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Essays on Macroeconomic Asymmetry and UK Labour Markets

submitted by

Magdalyn Okolo

for the degree of Doctor of Philosophy

University of Bath
Department of Economics

January, 2021

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"I am God, and there is no other; I am God, and there is none like me. I make known the end from the beginning, from ancient times, what is still to come."

Isaiah 46, 9-10.

Contents

Declaration

I, Magdalyn Okolo, confirm that the work presented in this thesis is my own. Where the research was carried out alongside others, or where information has been derived from other sources, I confirm that this has been indicated in the thesis. This work has not been submitted for any other degree or professional qualification.

Acknowledgement

I thank my family for their love, patience and support throughout my study. I thank Chris Martin; there is no better supervisor. I also thank Nikolaos Kokonas, my colleagues and the staff of the Department of Economics for their feedback on my research. Finally, I will always be grateful to the Department of Economics, University of Bath for funding my study, I have achieved an aspiration.

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Abstract

This thesis contains four chapters. Chapter One presents an introduction to the chapters that follow. Chapters Two to Four each have a distinct research focus with an underlying New Keynesian dynamic stochastic general equilibrium framework. Chapters Two and Three build on earlier collaborative research with Chris Martin. In Chapter Two, I use Behavioural theory to explain nonlinearities in the UK macroeconomy. Chapter Three presents a search frictions model of graduates and non-graduates in the UK labour market, simulating the differing impacts of the COVID-19 pandemic on both categories of worker. Chapter Four discusses the implications of the rising gig economy for wages and output in the UK.

Behavioural Downward Wage Rigidity and Macroeconomic Nonlinearity

A growing body of evidence suggests that the macroeconomy is not linear: shocks have a stronger impact on output in recessions than in expansions, negative shocks have a stronger impact on output than positive shocks of the same magnitude, large and small shocks have disproportional impacts on output, inflation and the real wage. To explain this, I develop a New Keynesian model with downward real wage rigidity, which I motivate using behavioural arguments. Workers experience disutility from exerting effort during production, but they also derive satisfaction from exerting effort when they feel 'fairly' treated by the firm. These behavioural elements generate the downward real wage rigidity which implies a convex Phillips Curve that is flatter when the output gap is negative. In the model, the intersection of the aggregate demand curve with this convex Phillips Curve generates nonlinearity that matches the empirical evidence.

To demonstrate non-linearity and asymmetry, I simulate the impacts of small and large, and positive and negative aggregate demand shocks. The results suggest that high inflation can be beneficial; the Phillips curve being steeper when the output gap is positive and flatter when the output gap is negative implies that at moderately high levels of inflation, much higher levels of output can be attained.

Modelling the Differing Impacts of COVID-19 in the UK Labour Market

Due to the actual and potential loss of life from the COVID-19 virus outbreak, the UK government announced a nationwide Lockdown in March, 2020. Businesses were closed, movement was restricted and many workers began working from home, albeit with reduced productivity. Workers who were unable to work from home were faced with job loss and the data shows marked differences in the impact of the pandemic across different sectors and types of worker. We model the impact of the pandemic on graduates and non-graduates in the UK. We use a model that is designed around key features of the UK labour market, which we simulate using shocks designed to mimic the pandemic. The model predicts that non-graduates would face more adverse impacts of the pandemic than graduates: about 1.2 million non-graduates would lose their jobs by the end of 2020, compared to 0.4 million for graduates, and by the end of 2020Q3, about 2 million non-graduates would be unemployed, compared to below 1million graduates.

The chapter describes the differing labour market experiences of different types of worker in the UK Labour market during the COVID-19 pandemic, and highlights the importance of accounting for segmented markets in policy-making.

The Impact of the Rising Gig Economy on UK Wages and Output

The nature of work in the UK is changing. Before the last 30 years, gig work was an option for firms to temporarily cut costs or respond to macroeconomic shocks, and for workers between traditional employment or to earn additional income. Now, gig work is becoming the 'new normal'; compared to the EU, the UK has the highest proportion of the workforce engaged in some form of gig work and the number continues to rise. I examine the implications for wage and output growth.

I construct a dual labour market search frictions model that describes the increasing distinction between the gig and traditional sectors in the UK. The model explains the difference in the wage for the same type of job between the traditional and gig sectors. I show that the rising gig economy can explain the UK's slow wage and output growth in the past decade. The results also support the evidence that gig work can be a stepping stone to traditional employment and vice versa, but it makes job-finding difficult for the unemployed. The results also show that the presence of the gig economy in the UK changes the macroeconomic response to shocks and can potentially reduce the effectiveness of policies.

1 Introduction

This chapter presents an overview of the concepts and models discussed in Chapters Two, Three and Four.

In Chapter Two, I discuss the convex Phillips Curve and macroeconomic nonlinearities. Since the past four decades, there has been growing evidence that the Phillips Curve has flattened (Borio and Filardo (2007), Coibion and Gorodnichenko (2015)), is nonlinear and convex (Debelle and Laxton (1997), Gagnon and Collins (2019)). Convexity implies that the Phillips Curve is steeper during periods of expansion and flatter in downturns. There is also evidence that the macroeconomy is not linear: shocks have a stronger impact on output in recessions than in expansions (Mandler (2012)), negative shocks have a stronger impact on output than positive shocks and the impact of large shocks are disproportional to those of small shocks (Ravn and Sola (2004)). Furthermore, output tends to fall more than it tends to rise (McKay and Reis (2008)), and the reverse is observed with the real wage (Abbritti and Fahr (2011)). In a linear macroeconomy, these differences are absent.

There is widespread evidence of the relationship between wage rigidity and the convex Phillips Curve. Downward wage rigidity implies that wages fall by less in response to a reduction in the output gap than they increase in response to an increase in the output gap of the same size. This imact of wage rigidity is transferred through the marginal cost to inflation, resulting in a Phillips Curve that is convex. The model in Chapter 2 combines Behavioural theory with the standard Dynamic Stochastic General Equilibrium (DSGE) model to explain the evidence outlined above. I adopt evidence in the Behavioural Literature that: *i*) workers derive disutility from exerting effort on the job, *ii*) the amount of effort workers exert depends on the wage, *iii*) workers have a wage which they feel entitled to, this is the *fair wage*, *iv*) workers are more inclined to increase their fair wage than to decrease it, *v*) workers feel fairly treated by the firm when the firm pays a wage that is above the fair wage, *vi*) when workers feel fairly treated by the firm, they exert reciprocity effort, and *vii*) workers are averse to reductions in the wage and this impacts effort (Akerlof and Yellen (1990), Bewley (2004)). The model describes how these features shape the macroeconomy, resulting in real wage rigidity, nonlinearity and asymmetry.

This chapter contributes to the Literature in two ways: Most models on wage rigidity, macroeconomic nonlinearities and the convex Phillips Curve often assume that real wage rigidity is derived from nominal wage rigidity without detailed derivations and explanations (eg Benigno and Ricci (2011)). In this chapter, I follow the evidence and propose that real wage rigidity generates nominal wage rigidity. The model in this chapter shares features with other behavioural DSGE macroeconomic models, such as Danthine and Kurmann (2010), Dickson and Fongoni (2019), Eliaz and Spiegler (2014) and Martin and Wang (2018). I incorporate evidence from the Behavioural Literature into a standard New Keynesian DSGE model to derive a Phillips Curve and macroeconomic nonlinearities that match the data.

Chapters Three and Four also use DSGE models, but have a different research focus. Both chapters combine search and matching theory with DSGE models. Chapter Three analyses the different experiences of graduates and non-graduates in the UK Labour Market during the COVID-19 pandemic. The shocks due to the pandemic and Lockdown have affected the whole economy, but have been more severe in sectors with a greater number of non-graduate roles. Fig. 1.1) shows the percentage of graduates and non-graduates in the different sectors in the UK in 2017Q3. The chart shows a greater number of non-graduates in the hospitality, manufacturing, construction and transportation sectors. These sectors also have higher numbers of at-risk jobs, jobs which cannot be performed remotely, and jobs which provide non-essential services which were subject to complete closure during the nationwide Lockdown.

In addition, data from the Office for National Statistics[1] show that graduates in the UK have higher average earnings and a higher employment rate than non-graduates, and about half of the employed graduates are in non-graduate roles. Expectedly, the data show that non-graduates in the UK are

[1]See ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/graduatesintheuk labourmarket/2017.

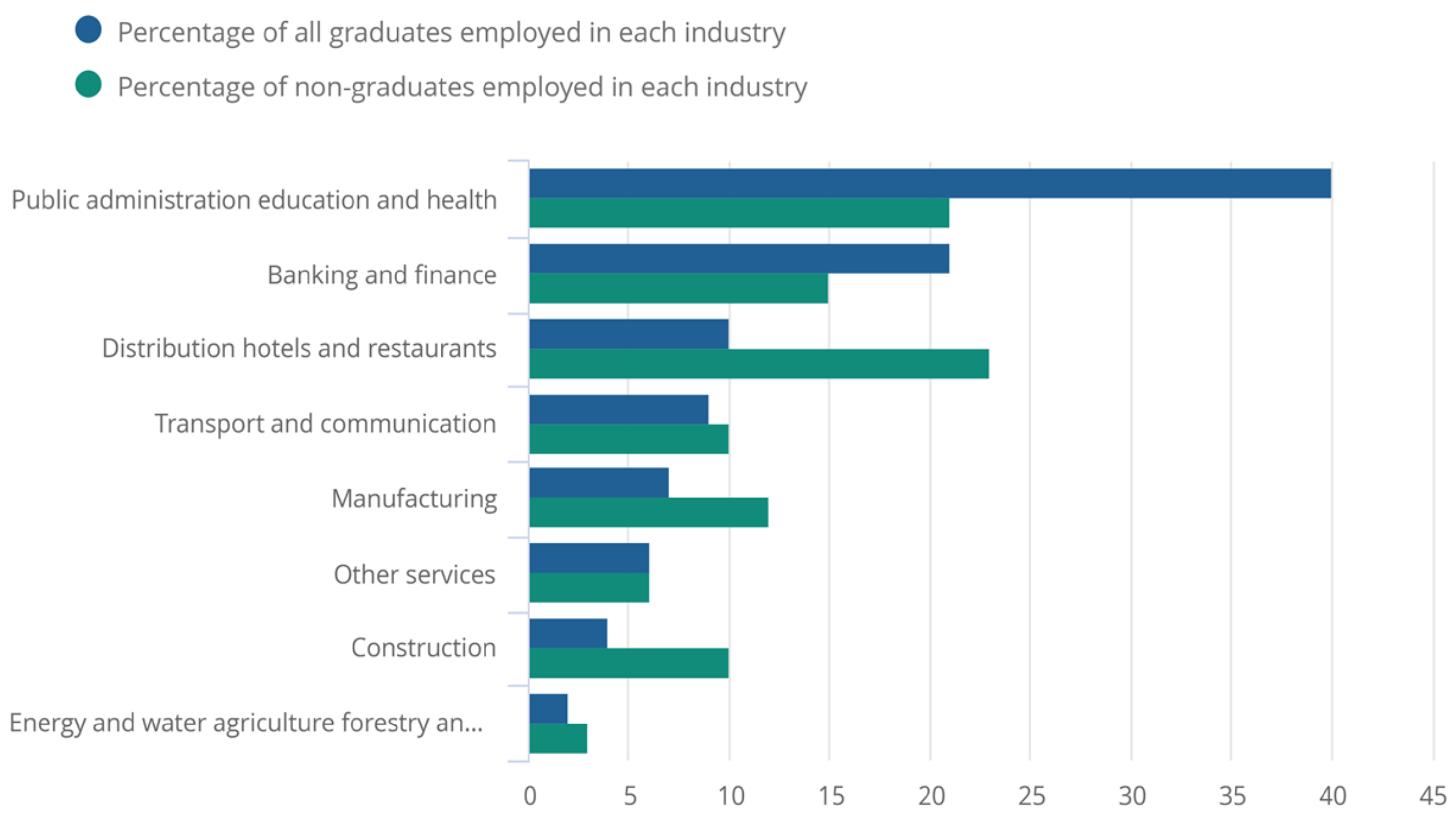


Figure 1.1: UK Graduate and Non-Graduate Employment by Sector

Note: Figure adapted from the Office for National Statistics: ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/graduatesintheuklabourmarket/2017.

more likely to be unemployed than graduates. These evidence have meant that non-graduates, who are normally in less secure and lower-paying jobs than graduates, have faced more severe impacts of the pandemic.

The model in Chapter Three describes the flows of graduates between graduate and non-graduate roles, and the movement of non-graduates across non-graduate roles. Using early projections for GDP and unemployment to calibrate the different shocks in the model, the differing impact of the pandemic on graduate and non-graduate wages, employment and unemployment becomes clear.

There have been many research contributions on the impact of the pandemic, including Susceptible-Infectious-Recovered (SIR)-DSGE models (eg Eichenbaum et al. (2020)), and DSGE models with adverse demand and supply shocks (eg Mihailov (2020), Guerrieri et al. (2020)). The model presented in this chapter differs from others in the pandemic literature in two major ways: it describes the impact of the pandemic on an economy with segmented labour and goods markets, and the pandemic is modelled as a combination of aggregate demand and supply shocks, including shocks specific to the labour market. The pandemic has uncovered the disparities between different workers and jobs in the UK, and this chapter attempts to address this. The results show that non-graduates are more severely affected by the pandemic than non-graduates. The model can serve as a template for examining the impacts of targeted government policy and public health measures, and the paths to economic recovery for the UK.

The final chapter discusses the rise in the UK gig economy. As shown in Fig. 1.2), there is a rising trend in UK lone-working self-employment, people working part-time because they are unable to find full-time employment, freelancers and contractors, agency and zero-hour contract workers. These workers often engage in temporary, on-demand or non-employee work arrangements which are collectively called gig work.[2]

Unlike the more traditional type of employment, gig jobs are characterised by high flexiblility and high turnover, often require low skills and offer low pay. Chapter Four discusses the factors driving the UK gig economy, the flows of workers between gig work and traditional employment and the implications for aggregate output and wages.

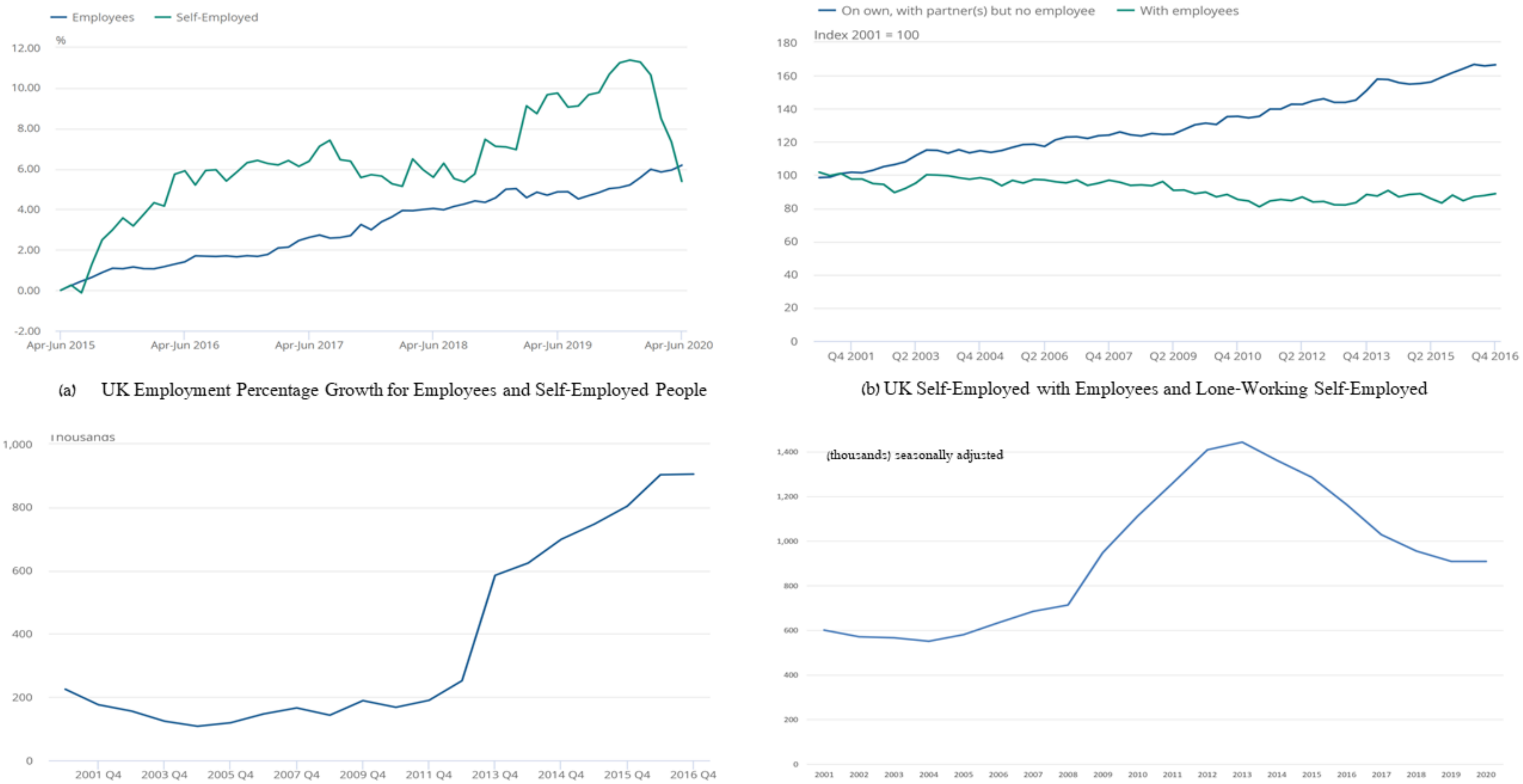
A significant amount of study has been done on gig work. However, most of these studies are in form of surveys and reports,[3] and often focus on online or app-based gig jobs. In this chapter, I attempt to capture the entire gig economy by including both online and offline gig workers. Secondly, academic rersearch on the gig economy and the impact on the macroeconomy are less common, and have mostly been done on the US labour market (eg Bracha and Burke (2016; 2021). I use the UK Labour Force Survey data to construct a two-sector model that describes the gig and traditional sectors of the UK. I use the model to explain why gig workers earn lower wages than traditional workers doing the same type of job, and show that the gig economy may help explain the slow wage and output growth in the UK in the past decade.

The results show that the presence of the gig economy changes the macroeconomic response to shocks. The model shows that gig workers earn a lower wage than traditional workers doing the same job because of differences in bargaining power, productivity and hiring costs. The results suggest that the moderating impact of shocks due to the presence of the gig economy can reduce the effectiveness of policies. The results also show that, in line with the evidence (eg in Booth et al. (2002)), gig work can be a stepping-stone to traditional work and vice versa, might reduce unemployment, but would potentially reduce wages and the quality of work as the gig economy expands.

At the end of this thesis, the reader would have been presented with three DSGE models varying in

[2]Workers who hold part-time jobs because they cannot find full-time work are included in this category because of the evidence that these workers often hold multiple part-time jobs which do not always add up to full-time employment (Bell and Blanchflower (2011), Bell and Blanchflower (2018*b*)).

[3]For example, The Good work: The Taylor Review of Modern Working Practices by Taylor et al. (2017), surveys by the Chartered Institute of Personnel Development (CIPD) and the Department for Business Innovation and Skills (DBIS).



(a) UK Employment Percentage Growth for Employees and Self-Employed People

(b) UK Self-Employed with Employees and Lone-Working Self-Employed

(c) UK Zero-Hour Contract Workers

(d) UK Part-Time Workers who want Full-Time Jobs

Figure 1.2: The Rising Trends in Gig Working in the UK

Note: Figures adapted from the Office for National Statistics: (a) ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/employmentintheuk/august2020, (b) ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/trendsinselfemploymentintheuk/2018-02-07, (c) ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/articles/contractsthatdonotguaranteeaminimumnumberofhours/mar2017, and (d) https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/datasets/fulltimeparttimeandtemporaryworkersseasonallyadjustedemp01sa.

application and complexity. The reader would understand the relationship between wage rigidity and macroeconomic nonlinearities, be familiar with the Behavioural Literature on fair wages, worker effort and reciprocity, and understand how these can impact the macroeconomy. The reader would encounter slightly more complex DSGE models later in the thesis, with labour market search frictions The reader would gain insight into the segmented nature of the labour and goods markets which make up the UK economy, the possible implications for workers, firms and policy-makers during adverse macroeconomic conditions such as the COVID-19 pandemic, and in the long term.

2 Behavioural Downward Wage Rigidity and Macroeconomic Nonlinearity

Appendix 6B: Statement of Authorship

This declaration concerns the article entitled:	
Behavioural Downward Rigidity and Macroeconomic Nonlinearity	
Publication status (tick one) **Draft manuscript** [X] **Submitted** [ ] **In review** [ ] **Accepted** [ ] **Published** [ ]	
Publication details (reference)	
Copyright status (tick the appropriate statement) I hold the copyright for this material [X] Copyright is retained by the publisher, but I have been given permission to replicate the material here [ ]	
Candidate's contribution to the paper (provide details, and also indicate as a percentage)	The candidate contributed to / considerably contributed to / predominantly executed the… Formulation of ideas: The ideas in this chapter were formulated during earlier joint work conducted with Prof. Chris Martin. My contribution to the formulation of the ideas used in this research is 50%. Design of methodology: 75% Experimental work: 80% Presentation of data in journal format: 80%
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.

Signed		**Date**	2/2/21

Note: This chapter builds on earlier joint work conducted with Chris Martin, who is a Professor of Economics at University of Bath, cim21@bath.ac.uk. The research is included in this thesis with his consent.

2.1 Introduction

A growing body of evidence suggests that the macroeconomy is not linear. This evidence includes studies that find that monetary policy shocks have a stronger impact on output in recessions than in expansions (eg Mandler (2012)) and that negative monetary and fiscal policy shocks have a stronger impact on output than positive shocks (eg Barnichon and Matthes (2014), Fazzari et al. (2015) and Ravn and Sola (2004)). There is also evidence that the impact of shocks is size-dependent, so the impact of large shocks is not proportional to the impact of small shocks (eg Balke (2000) and Mittnik and Semmler (2013)). A third strand in the literature has highlighted the negative skew of output growth (eg McKay and Reis (2008), Sichel (1993)) and the positive skew of inflation and the real wage (eg Abbritti and Fahr (2011), Adjemian et al. (2016)).

To explain this evidence, this chapter presents a New Keynesian model with downward real wage rigidity, motivated using behavioural arguments. Downward real wage rigidity implies a convex Phillips Curve, flatter when the output gap is negative. In the model, intersection of the aggregate demand curve with this convex Phillips Curve generates nonlinearity that matches the empirical evidence.

The convex Phillips Curve was proposed by Akerlof, Dickens and Perry (1996) and Debelle and Laxton (1997).[1] More recent studies in Babb and Detmeister (2017), Doser et al. (2017), Gagnon and Collins (2019), Gross and Semmler (2019), Hooper et al. (2019), Nalewaik (2016) and Santoro et al. (2014) provide further evidence of convexity.

There is widespread evidence of the relationship between wage rigidity and the convex Phillips Curve. Downward wage rigidity implies that wages fall by less in response to a reduction in the output gap than they increase in response to an increase in the output gap of the same size. As a result, deviations of the wage from their steady-state value are a convex function of the output gap. If wages are the main driver of a firm's marginal cost, this implies that the New Keynesian Phillips Curve is convex. But the evidence of real and nominal wage rigidities is less definitive. For instance, Babecky et al. (2010), Holden and Wulfsberg (2009) and Messina et al. (2010) find evidence of both real and nominal wage rigidities, but stronger evidence for nominal wage rigidity, Fagan and Messina (2009) find evidence of real and nominal wage rigidities to varying degrees in different countries,[2] Caju et al. (2009) support the evidence for real wage rigidity, but Martins et al. (2019), Stűber (2017) and Schaefer and Singleton (2019) find that real wages are not rigid. In addition, where real wage rigidity is proposed in the literature, the explanations are problematic. Downward real wage rigidity is assumed to be caused by downward nominal wage rigidity. In a prominent paper in the literature, Benigno and Ricci (2011) demonstrate the long-run trade-off between wage inflation and the output gap where the Phillips Curve is non-linear.[3] They assume that nominal wages are chosen by workers, and rigidity arises because workers cannot choose to reduce their wage. In their paper, downward rigidity is exogenous, citing links to fairness and wage norms. Others assume that workers face periodic wage-setting constraints (Daly and Hobijn

[1] There are other views Coen et al. (1999) and Stiglitz (1997) argue for concavity, while Eisener (1997, 1998) and Corrado and Holly (2003) argue that the Phillips curve is convex when unemployment is low but concave when it is high. Others (eg Gordon (1997) and Mussoa et al. (2009) argue that evidence for nonlinearity is not strong.

[2] Fagan and Messina (2009) find evidence of nominal wage rigidity in the US, Germany and Portugal, but for Finland and Belgium, they find strong evidence of real wage rigidity and little evidence of nominal wage rigidity.

[3] The trade-off between output an inflation implies that an economy can lower inflation by temporarily lowering output, and vice versa. This trade-off is more pronounced when the Phillips Curve is non-linear. For example, if the Phillips Curve is convex, during periods of low inflation, an increase in inflation would yield a greater increase in output, meaning that significant output growth can be achieved with lower cost to inflation. It also implies that high inflation can be reduced with low costs to output. See Akerlof, Dickens, Perry, Gordon and Mankiw (1996) for detailed discussion.

(2014)), that there are asymmetric costs to wage adjustments (Fagan and Messina (2009)), or that the wage depends on the past wage and is inflexible downwards (Dupraz et al. (2019)). But the source of these constraints on wage adjustment are not clearly explained. In the absence of a reason for these constraints, existing models of a convex Phillips Curve are somewhat arbitrary.[4]

I follow the literature in explaining the convex Phillips Curve with downward real wage rigidity. I adopt evidence from the Behavioural Literature and provide an alternative motivation for downward real wage rigidity.[5] I assume that workers experience disutility from exerting effort but also derive intrinsic satisfaction from working. I use the approach developed by Danthine and Kurmann (2010) to model reciprocity towards employers. However, as will be discussed below, this framework is also consistent with other reasons for intrinsic satisfaction, including utility derived from doing meaningful work and adhering to moral standards (eg Mazar et al. (2008)), adhering to social norms (eg Benabou and Tirole (2006)), from impure altruism (eg Andreoni (1989)) or from signaling pro social behaviour (eg Frey and Meier (2004)).

I assume that workers evaluate their labour market experience relative to a reference "fair wage"; an amount to which they feel entitled (Akerlof (1982), Akerlof and Yellen (1990), Bewley (1999), Goodman (1974), Kahneman and Tversky (1979), Kahneman et al. (1986)).[6] Survey evidence indicates that worker morale increases when they receive a "generous wage" offer from the firm, that is, a wage offer that is greater than the fair wage (Bewley (1999), Bewley (2004)). The evidence also shows that the impact of worker morale on output is not only from greater speed of work, but also from workers willingness to perform additional tasks, exert effort without supervision and induce co-workers to act similarly (*ibid.*). These confirm a positive relationship between fair wages, morale, reciprocity effort and output. Therefore, I assume that output depends on effort exerted by workers, but is not observable by firms.

Put together, these evidence imply that effort is an increasing function of the difference between the wage and the fair wage, and workers and firms are disinclined to wage reductions. To model this, I assume that employed workers feel entitled to a share of the surplus generated by their employment and therefore, the fair wage is pro-cyclical. It also becomes clear that the wage has a dual role in this model; it guides the allocation of labour, but it also motivates the worker to provide effort. The firm makes take-it-or-leave-it wage offers to workers that reflect this dual role. The wage balances the cost of the increased wage bill against the benefits from increased effort at the margin. In this simple model, this results in the wage being set as a mark-up over the fair wage.

Inflation is determined by the New Keynesian Phillips Curve. Inflation depends on movements in the real wage around steady-state and hence on movements in the fair wage around steady-state. The behavioural literature shows that the fair wage increases more readily than it falls. Evidence for this includes Agell and Lundborg (2003), Bewley (1999), Bewley (2007), Blinder and Choi (1990), Campbell and Kamlani (1997), Chemin and Kurmann (2012), Galuscak et al. (2012), and Millard and Tatomir (2015). This implies that movements in the fair wage around the steady-state are asymmetric; the fair wage responds more strongly when the output gap rises than when it falls. So movements in the fair wage and the real wage around steady-state are a convex function of the output gap. This results in real wage rigidity and a convex Phillips Curve.

[4] In a related model, Abbritti and Fahr (2011) assume that nominal wages are determined through worker-firm bargaining where there are asymmetric adjustment costs which imply that where it is more costly to reduce wages than to increase them. The rationale for these asymmetric adjustment costs is not explained.

[5] Some of the literature has suggested that fairness issues underlie downward rigidity; for example Abbritti and Fahr (2011) suggest that "the downward-rigidity constraint is purely exogenous in this model and could be rationalized by considering every worker as associated with a union that does not allow the wage to decline for reasons related to fairness and social norms".

[6] Evidence for the importance of fair wages includes experimental studies such as Brown et al. (2004), Camerer (2003) and Fehr et al. (2011), as well as other studies such as Cohn et al. (2014), Gneezy and List (2006) and Krueger and Mas (2004). See Della Vigna (2009), Dickson and Fongoni (2019) and Fehr et al. (2009) for surveys of the evidence and Martin and Wang (2018) for further discussion.

The model shares features with other behavioural DSGE macroeconomic models, such as Campbell (2008), Danthine and Donaldson (1990), Danthine and Kurmann (2010), de La Croix et al. (2009), Kuang and Wang (2017) and Vaona (2013). But these models do not derive a convex Phillips Curve; rather, they express the fair wage as a function of current and lagged values of productivity, output and unemployment. This approach generates substantial macroeconomic persistence, but not the type of nonlinearity I analyse in this paper. Dickson and Fongoni (2019) model the concepts of fairness, effort, morale, reciprocity and downward wage rigidity, but also do not derive a Phillips Curve. Eliaz and Spiegler (2014) and Martin and Wang (2018) incorporate these behavioural concepts into a search-and-matching model to explore the implications for equilibrium wage and unemployment; the modeling of effort and the supply side of this model is similar to the behavioural search frictions model in Martin and Wang (2018).

To illustrate how the mechanism underlying the model generates nonlinear movements in the output gap and inflation that match empirical evidence, I compare the impact of equally-sized positive and negative shocks to demand on an economy that is in steady-state. The positive shock to aggregate demand increases output. The fair wage of workers increases. Firms respond by increasing the real wage. This leads to increased inflation. The negative shock leads to reduced output, a lower fair wage, a reduction in the real wage and lower inflation. However, the increase in the output gap increases the fair wage by more than the reduction in the output gap reduces it. This asymmetric response of the fair wage results in a stronger response of the output gap to a negative shock than to a positive shock, whereas inflation responds more to a positive shock than a negative shock. This is consistent with the evidence of differing impacts of positive and negative shocks discussed above, with the evidence of a negative skew to the output gap and with evidence of a positive skew to inflation and the real wage. This mechanism also implies that a large positive shock will result in a proportionately larger response of inflation and a proportionally smaller response of the output gap; this is consistent with the evidence on the size-dependent impact of shocks.

2.2 The Model

2.2.1 Households

The utility of a representative household is

$$H_t = \sum_{k=0}^{\infty} (\beta e^{\varepsilon^d_{t+k}})^k \left\{ \frac{C_{t+k}^{1-\eta}}{1-\eta} - N_{t+k}\Big(\frac{\Theta e_t^{1+\varphi}}{1+\varphi} - \frac{\nu e_t^{1-\chi}}{1-\chi}(w_t - w_t^{fair}) \Big) \right\} \tag{2.1}$$

where C is household consumption of retail goods and η is the intertemporal elasticity of consumption, N is the number of household members who are employed, w is the real wage, w^{fair} is the fair wage and e is the amount of effort exerted by employed household members. β and e^{ε^d} represent the discount factor and a preference shock respectively. Θ and ν are coefficients on the disutility of exerting effort and utility of reciprocity effort respectively, φ represents the elasticity of the household's disutility from exerting effort, while χ is the elasticity of reciprocity effort where $\varphi > 0$, $\chi > 0$ and $\varphi + \chi > 1$.

Households derive utility from consumption. Each employed household member experiences disutility from exerting effort, given by $D(e_t) = \frac{\Theta e_t^{1+\varphi}}{1+\varphi}$. Assuming $\varphi > 0$ implies there is an increasing marginal disutility of exerting effort. Each employed household member also gains utility from a reciprocity response to the wage offered by the firm, given by $R(e_t, w_t - w_t^{fair}) = \frac{\nu e_t^{1-\chi}}{1-\chi}(w_t - w_t^{fair})$, where $g(w_t - w_t^{fair}) = (w_t - w_t^{fair})$ is the household's perception of the generosity of the wage offer of the firm and $d(e_t) = \frac{\nu e_t^{1-\chi}}{1-\chi}$ is the reciprocal effort response of the household following Koszegi and Rabin (2006) and Rabin (1993). The assumption that $\chi > 0$ ensures the reciprocal response is a convex function of effort.

The household budget constraint is

$$P_t w_t N_t + P_t b(1 - N_t) + \Pi_t + B_{t-1} = P_t C_t + T_t + q_t B_t \tag{2.2}$$

where P is the nominal price index for retail goods, w_t is the real wage, b is real unemployment benefit, Π is the household's share of profits, B are one-period bonds, T is a lump-sum tax and q is the nominal price of bonds. The household determines consumption, how many bonds to hold and how much effort its employed members will exert.

Combining the first-order conditions for consumption and bond purchases gives

$$C_t^{-\eta} = \beta e^{\varepsilon_t^d} E_t C_{t+1}^{-\eta} \frac{1 + i_t}{1 + E_t \pi_{t+1}} \tag{2.3}$$

where i is the nominal interest rate defined by $q = \frac{1}{1+i}$ and π is the inflation rate. Defining the real interest rate as $1 + r_t = \frac{1+i_t}{1+E_t\pi_{t+1}}$, this implies that

$$E_t \beta_{t,t+1} = \frac{1}{1 + r_t} \tag{2.4}$$

where $E_t\beta_{t,t+1} = \beta e^{\varepsilon_t^d} \frac{E_t C_{t+1}^{-\eta}}{C_t^{-\eta}}$ is the stochastic discount factor,

Household consumption of retail goods is a composite of individual retail goods defined by $C_t = (\int_0^1 (C(j)_t)^{\frac{\epsilon-1}{\epsilon}} dj)^{\frac{\epsilon}{\epsilon-1}}$, where $C(j)$ is household consumption of retail good j and ϵ is the elasticity of substitution between the differentiated retail goods. The corresponding nominal price index is $P_t = (\int_0^1 P(j)_t^{1-\epsilon} dj)^{\frac{1}{1-\epsilon}}$ where $P(j)$ is the nominal price of retail good j. The demand of the household for retail good j is

$$C(j)_t = \left(\frac{P(j)_t}{P_t}\right)^{-\epsilon} C_t \tag{2.5}$$

Since all output is consumed, the demand for good j is $Y(j)_t$, given by

$$Y(j)_t = \left(\frac{P(j)_t}{P_t}\right)^{-\epsilon} Y_t \tag{2.6}$$

Although the model follows the approach of Danthine and Kurmann (2007) in deriving the optimal effort, the effort function is different as the specifications of the $g(w_t)$ and $d(e_t)$ in this model are different. Here, households choose effort to maximise their utility function in (1), so the optimal level of effort satisfies $D_e(e_t) = R_e(e_t, w_t)$. Optimal effort is

$$e_t = \xi(w_t - w_t^{fair})^{\sigma} \tag{2.7}$$

for $w_t - w_t^{fair} > 0$ and $e_t = 0$ for $w_t - w_t^{fair} \leq 0$, where $\sigma = \frac{1}{\varphi+\chi}$ and $\xi = (\frac{\nu}{\omega})^{\sigma}$. This effort function is widely used in the literature, including in Garino and Martin (2000), Heijdra (2017), Knell (2014), Martin and Wang (2018), Romer (2006), and Summers (1988). It is consistent with the argument in Kahneman and Tversky (1979) that the sensitivity of effort to the wage should be larger when the wage is closer to the fair wage. The assumption that $\varphi + \chi > 1$ implies that the effort function is concave. Effort functions similar to (2.7) have been estimated by Della Vigna and Pope (2018). They estimate a low value for σ, indicating that the effort function is highly concave. Fig. 2.1) illustrates the implications of the concave effort function that effort is more sensitive at small values of $w_t - w_t^{fair}$.

An alternative approach used in the literature (eg Dickson and Fongoni (2019)) model the optimal effort as a piece-wise function in which workers exhibit positive, normal and negative reciprocity effort

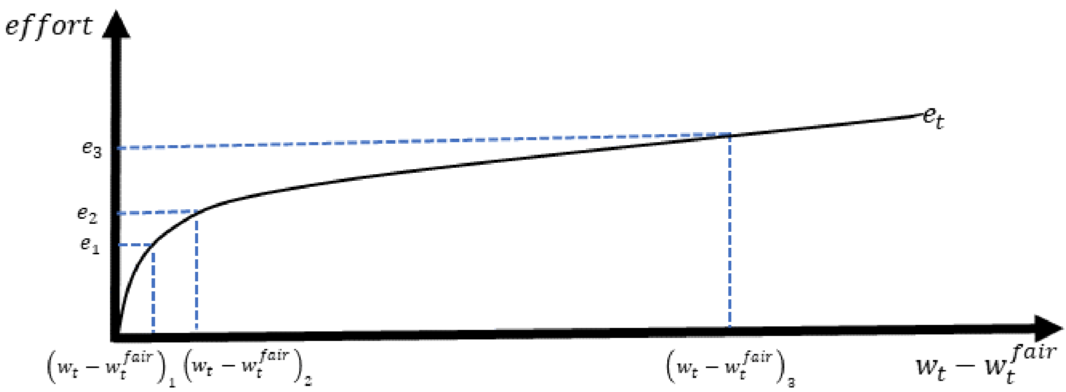


Figure 2.1: The Effort Function

The concavity of the effort function is determined by σ. The figure shows a strong effort response when the difference between the wage and the fair wage is small, and the reverse when the difference is large.

in response to wage offers which are higher, equal or lower than the fair wage respectively. Another alternative is (eg Danthine and Kurmann (2010) and de La Croix et al. (2009)) is to assume that $D(e) = (e - e^*)^2$ without including reciprocity effects and so $e = e^*$. The effort function e^* is then specified using intuitive arguments. The approach used in this paper was chosen because of strong empirical evidence of reciprocity effects, and because the functional form implies a smooth, continuous effort function that is endogenous to the analysis. The Dickson and Fongoni (2019) approach implies a "kinked" effort function, and the other alternatives assume, implausibly, a constant marginal disutility of effort.

There are a number of measures of the fair wage in the Behavioural literature. Workers' perception of a fair wage can be based on their past wage (Kahneman et al. (1986)), a share of profits and the firm's ability to pay (Blanchflower and Oswald (1988), Hildreth and Oswald (1997)),[7] internal wage equity (Bewley (2004)), external wage equity, including through collective bargaining (Rees (1993)) and minimum wage policies (Koenig et al. (2020)). There is also evidence that workers use multiple measures to determine their fair wage (Goodman (1974), Kahneman (1992), Rees (1993)). The specification of the fair wage in this model is compatible with the different measures of the fair wage in the literature and the changes across the business cycle so that

$$w_t^{fair} = w_{ss}^{fair} e^{\gamma_0 (e^{\gamma \hat{y}_t} - 1)} \tag{2.8}$$

where w_{ss}^{fair} is the real value of the fair wage in steady-state and $e^{\gamma_0 (e^{\gamma \hat{y}_t} - 1)}$ is the loss aversion function in Kőbberling and Wakker (2005). This exponential component captures the asymmetric movement of the fair wage across the business cycle where $\hat{y}_t = \frac{Y_t - Y_{ss}}{Y_{ss}}$ is the output gap, Y_t is output and Y_{ss} is output in steady-state. This functional form implies $w_t^{fair} > w_{ss}^{fair}$ when the output gap is positive and $w_t^{fair} < w_{ss}^{fair}$ when the output gap is negative as shown in Fig. 2.2).

The fair wage being an asymmetric convex function of the output gap means that when the output gap is positive, a 1% increase in the output gap increases the fair wage by more than 1%, whereas, when the output gap is negative, a 1% reduction in the output gap reduces the fair wage by less than 1%.

[7] This is related to the principle of dual entitlement of Kahneman et al. (1986); firms feel entitled to a referent profit as workers feel entitled to a fair wage. Workers determine fairness by weighing their gains (their wage) against their losses (the firm's profit).

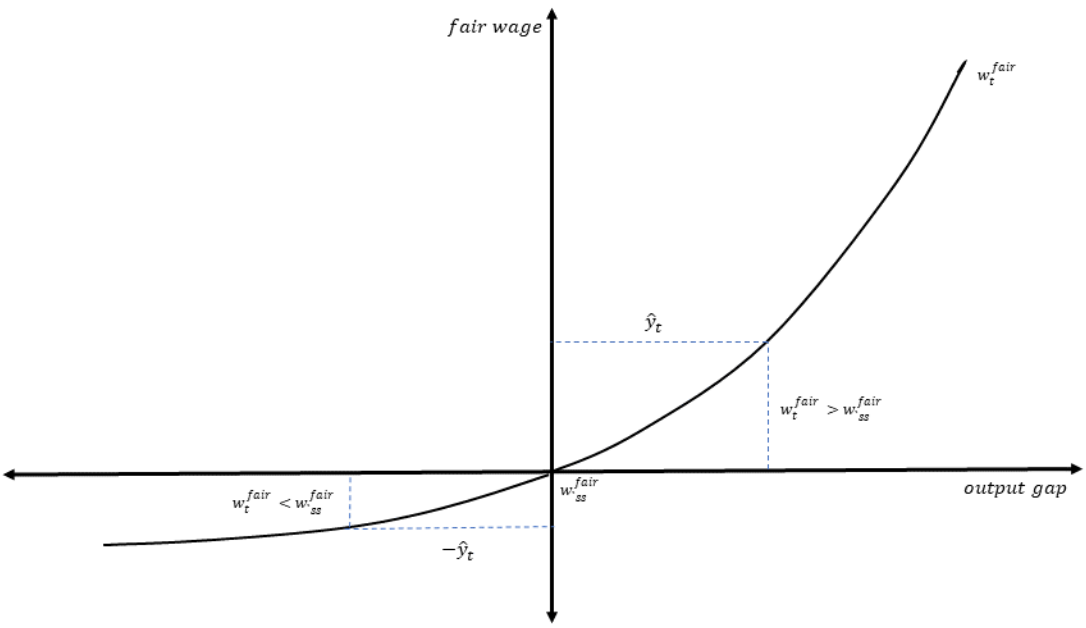


Figure 2.2: The Fair Wage

The fair wage falls when the output gap falls and increases when the output gap increases. The convexity of the fair wage curve is denoted by γ_0. In the diagram, $|-\widehat{y_t}|=\widehat{y_t}$; there is a sharp increase in the fair wage for $\hat{y}_t$, but for $-\hat{y}_t$, there is a smaller decrease in the fair wage. This is because the fair wage is linked to workers' standard of living and well-being, a measure of self-worth and their value to the firm (Bewley (1998)), and workers are loss averse (Kahneman et al. (1986), Tversky and Kahneman (1991)). The asymmetry is captured by γ.

The fair wage can be approximated as

$$w_t^{fair} = w_{ss}^{fair}(1 + \hat{w}_t^{fair}) \tag{2.9}$$

where $\hat{w}_t^{fair} = \frac{w_t^{fair} - w_{ss}^{fair}}{w_{ss}^{fair}}$. Using (2.8) and (2.9), the movement in the fair wage across the business cycle is approximately

$$\hat{w}_t^{fair} = \gamma_0(e^{\gamma \hat{y}_t} - 1) \tag{2.10}$$

The fair wage steady-state deviation is nonlinear. The specification of the fair wage in (2.8) implies that the fair wage increases more in response to an economic expansion than it falls in response to a contraction. This is further supported by Chemin and Kurmann (2012), who find empirical support for the argument in Bewley (2007) that workers quickly come to feel entitled to their wage. Also, the concavity of the effort function derived in (2.7) implies that effort is more responsive to reductions in the wage relative to the fair wage than to increases of the same size. Further evidence on this is provided by Kube et al. (2013), who found that wage cuts had a detrimental and persistent impact on productivity, but that equivalent wage increases did not result in any productivity gains. These characteristics of the fair wage and effort are taken into account when the firm determines the optimal wage offer.

2.2.2 Wholesale Firms

There is a continuum of identical wholesale firms on the unit interval. Wholesale firms use labour to produce identical wholesale goods. These are sold to retail firms on a competitive market. Their output depends on a technology shock, the number of workers employed and on the amount of effort exerted by workers. Wholesale firms determine employment and wages. Wholesale firms cannot determine the level of effort, rather they influence this through their choice of the wage. Thus wholesale firms can respond to an increase in demand along the extensive margin by increasing employment, or along the intensive margin by increasing the wage to induce increased effort. The assumption that firms cannot determine effort is in line with the literature on introducing behavioural effects into Real Business Cycle and New Keynesian models (eg Danthine and Donaldson (1990) and Danthine and Kurmann (2010) and distinguishes this approach from papers such as Gali and van Rens (2014) and Bils et al. (2014), in which effort is determined through worker-firm bargaining. The assumption that the wage is determined by wholesale firms rather than through worker-firm bargaining is consistent with behavioural macroeconomic models such as Danthine and Donaldson (1990), Danthine and Kurmann (2010), contributions such as Manning (2003), and the evidence that wage-posting is predominant in specific sectors or job types such as the public sector, large firms, part-time and contract work (Brenzel et al. (2014), Hall and Krueger (2008)).

The production function of wholesale firms is

$$Y_t^W = A_t N_t e_t \tag{2.11}$$

where Y^W is the output of the wholesale firm, A is a productivity shock common to all firms and I assume $A_t = e^{\varepsilon_t^s}$.

The objective function of a wholesale firm is

$$J_t^W = \sum_{k=0}^{\infty} \beta_{t,t+k} \Big\{ \frac{P_{t+k}^W A_{t+k} e_{t+k} N_{t+k}}{P_{t+k}} - w_{t+k} N_{t+k} \Big\} \tag{2.12}$$

where P^W is the nominal price of wholesale goods. The firm chooses the wage and employment, maximising (2.12) subject to the effort function in (2.7).

The first-order condition for employment is

$$\frac{A_t e_t}{\mu_t} = w_t \tag{2.13}$$

where $\mu_t = \frac{P_t}{P_t^W}$ is the price mark-up in the retail sector. This implies that the relative price of wholesale goods equals the inverse of the real marginal cost, since

$$\mu_t = \frac{1}{mc_t} \tag{2.14}$$

where $mc_t = \frac{w_t}{A_t e_t}$ is real marginal cost.

The optimality condition for the wage is

$$\frac{A_t e_w}{\mu_t} = 1 \tag{2.15}$$

where e_w is the derivative of effort with respect to the real wage. This balances the cost of a higher wage against the benefit, in the form of higher output, at the margin. This optimality condition can be written as

$$\Big(\frac{A_t e_t}{\mu_t}\Big)\Big(w_t \frac{e_w}{e_t}\Big) = w_t$$

Noting that the elasticity of effort with respect to the real wage is $w_t \frac{e_w}{e_t} = \sigma(\frac{w_t}{w_t - w_t^{fair}})$ and that the job creation condition implies $\frac{A_t e_t}{\mu_t} = w_t$, the optimality condition for the wage can be written as

$$\sigma w_t = w_t - w_t^{fair}$$

The wage chosen by the wholesale firm is therefore

$$w_t = \frac{1}{1-\sigma} w_t^{fair} \tag{2.16}$$

The wage offered by the firm is a markup on the fair wage. The wage depends on the fair wage through the effort effect, with the markup increasing as the sensitivity of effort to changes in the wage increases. Using (2.8), movements in the real wage across the business cycle are given by

$$\widehat{w}_t = \gamma_0(e^{\gamma \hat{y}_t} - 1) \tag{2.17}$$

Equation (2.17) exhibits the real wage rigidity that is the central mechanism driving this model: since the real wage is a convex function of the output gap,[8] an increase in the output gap leads to a larger increase in the real wage than the reduction in the real wage following a reduction in the output gap of the same size. Real wage rigidity arises because firms realise that the adverse effect of real wage reductions on productivity offset the benefits of a reduced wage bill and so respond to a reduced output gap by reducing the wage by less than they would do in the absence of fair wage considerations. Supporting evidence for this is provided by Galuscak et al. (2012), who present survey evidence for 15 EU countries showing that firms do not reduce wages in recessions because of the impact on effort. Similar findings in Blinder and Choi (1990), Bewley (1999), Agell and Lundborg (2003) and Millard and Tatomir (2015) show that this finding is robust.

2.2.3 Retail Firms

Retail firms purchase wholesale goods from wholesale firms in a competitive market and transform these costlessly into differentiated retail goods which they sell to households They face a downward-sloping demand curve and set the price of their output, subject to Calvo frictions on price adjustment.

Their production function is

$$Y(j)_t = Y(j)_t^W \tag{2.18}$$

where $Y(j)^W$ is the amount of the wholesale good purchased by retail firm j. Real marginal cost, given by (2.14), is the same for all retail firms. Retail firms can adjust their price in each period with probability $(1-\omega)$. In period t, they therefore choose their price, $P(j)_t$, to maximise

$$E_t \sum_{k=0}^{\infty} (\omega)^k \Big\{ \beta_{t,t+k} \Big(\frac{P(j)_t - P_{t+k}^W}{P_{t+k}} \Big) Y(j)_{t+k} \Big\} \tag{2.19}$$

subject to

$$Y(j)_{t+k} = \Big(\frac{P(j)_t}{P_{t+k}} \Big)^{-\epsilon} Y_{t+k} \tag{2.20}$$

Their optimal price is

$$\frac{P(j)_t^*}{P_t} = \mu(1-\beta\omega) E_t \sum_{k=0}^{\infty} (\beta\omega)^k \frac{P_{t+k}^W}{P_{t+k}} \tag{2.21}$$

where $P(j)_t^*$ is the price chosen by retail firm j at time t. In steady-state, the retail price is a mark-up $\mu = \frac{\epsilon}{\epsilon - 1}$ over marginal cost, the price of wholesale goods. Away from steady-state, the mark-up may vary due to frictions on price adjustment.

[8] The fair wage specification in this model implies a smooth wage curve similar to the Fig. 2.2). A piece-wise specification of the fair wage would result in a "kinked" wage-setting curve as described in Dickson and Fongoni (2019).

2.2.4 Monetary Policy

I assume that the nominal interest rate follows the simple Taylor rule

$$i_t = \bar{i} + \phi_\pi \pi_t + \varepsilon_t^i \tag{2.22}$$

where $\bar{i}$ is the steady-state interest rate, ϕ_π is the policy response to inflation and ε_t^i is a monetary policy shock. A rise in the interest rate will, from (2.3), reduce consumption in the current period relative to future consumption.

2.2.5 The Phillips Curve

Linearising the price relationship in (2.21) around a zero inflation steady-state gives the New Keynesian Philips Curve relationship (Gali and Gertler (1999))

$$\pi_t = \beta E_t \pi_{t+1} + \kappa \widehat{mc}_t \tag{2.23}$$

where $\kappa = \frac{(1-\omega)(1-\beta\omega)}{\omega}$. This relates inflation to the proportional deviation of the real marginal cost of retail firms around its steady-state value. Using the definition of real marginal cost, this is

$$\widehat{mc}_t = \widehat{w}_t - \widehat{e}_t - \varepsilon_t^s \tag{2.24}$$

Noting that $\widehat{w}_t = \widehat{w}_t^{fair}$ and $\widehat{e}_t = \sigma \widehat{w}_t^{fair}$, I obtain

$$\pi_t = \beta E_t \pi_{t+1} + \kappa \{(1-\sigma)\widehat{w}_t^{fair} - \varepsilon_t^s\} \tag{2.25}$$

Using (2.8), the resultant Phillips Curve is

$$\pi_t = \beta E_t \pi_{t+1} + \kappa \{(1-\sigma)\gamma_0 (e^{\gamma \hat{y}_t} - 1) - \varepsilon_t^s\} \tag{2.26}$$

Without effort and the behavioural features of the fair wage, the New Keynesian Phillips Curve relationship would be linear, similar to Gali and Gertler (1999), although the underlying mechanism and the structural parameters are different. The New Keynesian Phillips Curve in (2.26) is convex and asymmetric reflecting the adjustment of the fair wage across the business cycle. In common with other recent papers, such as Benigno and Ricci (2011) and Daly and Hobijn (2014), the model shows that downward real wage rigidities lead to a convex Phillips Curve, but differ from this literature in arguing that real wage rigidity originates from the workers perception of the fair wage at different points in the business cycle and the impact on effort.

2.3 Simulation Evidence

This section presents simulation evidence showing how the model derived in this paper is consistent with the empirical evidence discussed in the introduction. The model comprises the household intertemporal optimality condition in (2.3), the effort function in (2.7), the fair wage in (2.8), the production function in (2.11), the wage equation in (2.16), the monetary policy rule in (2.22), the Phillips Curve in (2.26) and the resource constraint $Y_t = C_t$.

2.3.1 Calibration

The calibrated parameters are reported in Table 2.1). Where possible, parameters are calibrated in line with the existing New Keynesian literature. I assume that retail firms are able to reset prices on average every four quarters, so $\omega = 0.75$. I use $\beta = 0.99$, $\eta = 1.5$ and $\rho_\pi = 1.5$. Della Vigna and Pope (2018) estimate an effort function similar to the optimal effort in (2.7). Based on their estimates, I calibrate $\sigma = 0.02$. I calibrate the convexity and asymmetry parameters $\gamma_0 = 0.045$ and $\gamma = 19$ respectively, so that the Phillips Curve in (2.26) matches the Gross and Semmler (2019) estimate for the slope of the Euro-area Phillips Curve which is 0.05 when the output gap is negative and 0.12 when the output gap is positive.

To examine the impact of positive and negative, and large and small demand shocks, I use $\varepsilon_t^d = \rho_d \varepsilon_{t-1}^d + \varrho_t^d$ and assume $\varrho_t^d = \iota_d$ for $t = 1$ and $\varrho_t^d = 0$ for other periods. A small positive demand shock is $\iota_d = 0.01$, a large positive demand using is $\iota_d = 0.02$, a small negative demand shock is $\iota_d = -0.01$ and a large negative demand shock is $\iota_d = -0.02$. The persistence of the demand shock is $\rho_d = 0.9$.

Table 2.1: Calibrated Parameters

Parameter	Interpretation	Value	Source
ω	Probability Wholesale Firm Cannot Reset Price	0.75	Gali and Gertler (1999)
β	Discount Factor	0.99	Gali and Gertler (1999)
η	Intertemporal Elasticity of Substitution	1.5	Gali and Gertler (1999)
ϵ	Elasticity of Substitution between Retail Goods	11	Gali and Gertler (1999)
σ	Elasticity of Effort Function $\left(\frac{1}{\varphi+\chi}\right)$	0.02	Della Vigna and Pope (2018)
ρ_π	Coeff. on Monetary Policy Rule	1.5	Author's Calculation
γ	Asymmetry of Fair Wage Function	19	Author's Calculation
γ_0	Convexity of Fair Wage Function	0.045	Author's Calculation
ρ_d	Demand Shock Persistence	0.9	Author's Calculation
ι_d	Small Positive Demand Shock	0.01	Author's Calculation
ι_d	Large Positive Demand Shock	0.02	Author's Calculation
ι_d	Small Negative Demand Shock	-0.01	Author's Calculation
ι_d	Large Negative Demand Shock	-0.02	Author's Calculation

The Phillips Curve implied by these calibrations is depicted in Fig. 2.3). There is little sign of asymmetry when the output gap is small. Asymmetry becomes prominent as output diverges from equilibrium by more than 1%, with very clear differences in the inflation rates generated by output gaps of 3% or more. This is consistent with evidence that inflation became less responsive to output during the post-2008 recession (eg Ball and Mazumder (2011), Blanchard (2016), and Cecchetti et al. (2017).

2.3.2 Simulation Results

The model is solved numerically under perfect foresight using the method of Fair and Taylor (1983).[9] The method assumes that the values of all shocks are known in advance. For a similar approach, see Lindé and Trabandt (2018). The results are shown in Figure 2.4). The left hand panel shows the responses of

[9]The Fair and Taylor (1983) method uses solutions of the nonlinear model rather using a linearisation of the model. This method is preferable because the Phillips Curve is close to being linear when the output gap is small and so a lineariation around the steady-state cannot capture the impact of the convex Phillips Curve.

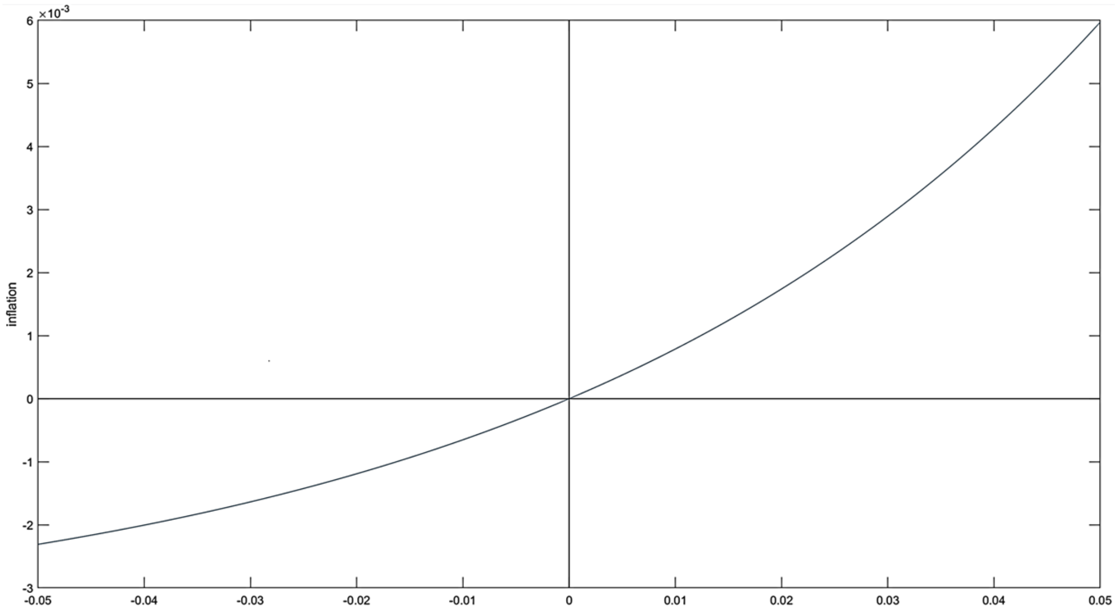


Figure 2.3: The Behavioural Phillips Curve
Convexity and asymmetry are transmitted from the fair wage to the wage, marginal cost and on to inflation. At $\gamma_0 = 0.045$ and $\gamma = 19$, the Behavioural Phillips Curve is convex and asymmetric.

the fair wage, the output gap and the inflation rate to the alternative demand shocks. The right hand panel shows the normalised impulse responses, where the impulse response is divided by the value of the shock.

The impulse responses show that positive demand shocks have a larger impact on the fair wage than negative shocks and a small negative shock has a proportionately larger effect than a large negative shock. Through this mechanism, the impulse responses of inflation and the output gap are able to match the empirical evidence discussed above. Negative demand shocks have a stronger impact on output than positive shocks, consistent with empirical evidence in Barnichon and Matthes (2014), Fazzari et al. (2015) and Ravn and Sola (2004). Large negative demand shocks have a proportionately stronger impact on output than small negative shocks, consistent with evidence in Balke (2000) and Mittnik and Semmler (2013). The output gap has a negative skew while inflation has a positive skew, consistent with evidence in Abbritti and Fahr (2011), Adjemian et al. (2016), McKay and Reis (2008) and Sichel (1993)).

2.4 Conclusions

This chapter brings together the New Keynesian and Behavioural literatures to provide a unified explanation for macroeconomic nonlinearities. Firms require workers to exert effort but effort is difficult to observe. Workers dislike exerting effort but will exert reciprocity effort when they feel that they are treated fairly by the firm. Incorporating these behavioural features into a simple New Keynesian model provides a tractable explanation for downward real wage rigidity that matches the behaviour of wages, output and inflation: in a downturn, wages do not fall because of fairness concerns and the impact on worker effort. This induces the asymmetric responses and skews on output and inflation.

Although there is strong evidence of nonlinearities in the macroeconomy, estimates of the nonlinearities are few. The model will benefit from more precise estimates of the convexity and asymmetry in both the New Keynesian and Behavioural Literatures. As the slope of the Phillips Curve in this model depends on behavioural factors, more precise calibrations of the behavioural factors that define convexity

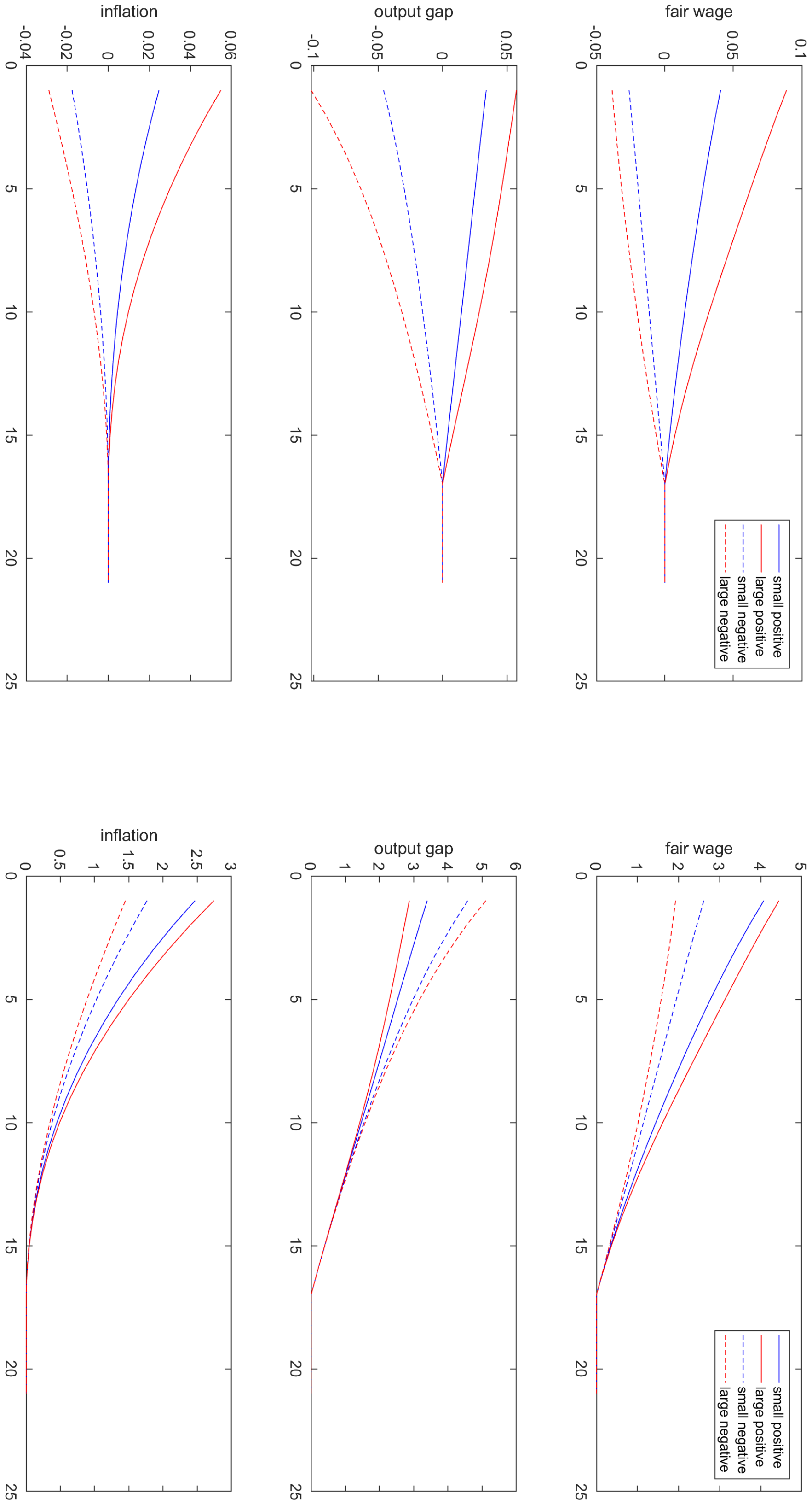


Figure 2.4: Impulse Responses to Demand Shocks

and asymmetry might make the model useful in explaining the evidence that the slope of the Phillips Curve changes or can seem to disappear (Hooper et al. (2020)). It also suggests that the inflation target may need to be adjusted if behavioural factors change. Fianlly, the results suggest that high inflation can be beneficial; the Phillips curve being steeper when the output gap is positive and flatter when the output gap is negative implies that at moderately high levels of inflation, much higher levels of output can be attained. Similar to Benigno and Ricci (2011), the model can be extended to analyse the impact of stabilisation policies and the output inflation trade-off.

3 Modelling the Differing Impacts of COVID-19 in the UK Labour Market

Appendix 6B: Statement of Authorship

This declaration concerns the article entitled:

Modelling the Differing Impacts of Covid-19 in the UK Labour Market

Publication status (tick one)

Draft manuscript		Submitted		In review	X	Accepted		Published	

Publication details (reference)	Oxford Bulletin of Economics and Statistics Manuscript ID OBES-20-324

Copyright status (tick the appropriate statement)

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Candidate's contribution to the paper (provide details, and also indicate as a percentage)	The candidate contributed to / considerably contributed to / predominantly executed the… Formulation of ideas: The ideas in this chapter were formulated during joint work with Prof. Chris Martin. My contribution to this was 50%. Design of methodology: 50% Experimental work: 50% Presentation of data in journal format: 50%
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.

Signed		**Date**	2/2/21

Last update: Feb 2019

Note: This chapter presents joint work with Chris Martin, who is a Professor of Economics at University of Bath, cim21@bath.ac.uk. The research is included in this thesis with his consent. A later version of the paper presented in this chapter is being revised for resubmission at the Oxford Bulletin of Economics and Statistics and is publicly available on the University of Bath research portal at https://researchportal.bath.ac.uk/en/publications/modelling-the-differing-impacts-of-covid-19-in-the-uk-labour-mark and on SSRN at https://papers.ssrn.com/sol3/papers.cfm?abstract˙id=3676400.

3.1 Introduction

The COVID-19 pandemic has severely disrupted economies across the world and put health care systems under enormous stress. This paper models the response of the labour market in the UK to the pandemic. The COVID-19 crisis has had a major impact on the UK labour market. At the peak of the pandemic, only around 50% of workers were at work and up to 10 million workers were furloughed as part of the Job Retention Scheme (JRS) (Leslie (2020), PWC (2020)). Two thirds of employers made use of the JRS. GDP fell by 20% in April 2020, and is widely forecast to be at least 10% lower in 2020 compared to 2019. Unemployment is forecast to rise to at least 3 million, or 9% of the workforce.[1]

We address the questions: How has the pandemic affected the labour market experience of different types of workers in the UK? And what is the likely adjustment process as the economy recovers? We address these questions using a DSGE model with labour market frictions, designed to reflect the UK labour market. We simulate this model using a series of shocks that are constructed to mimic the effects of the pandemic, and track the movements of output, employment, unemployment, job losses, wages and inflation over the course of the crisis. We adapt the models of Blanchard and Gali (2010), Thomas (2008) and Ravenna and Walsh (2011)[2] to allow for three key features of the UK labour market. First, the labour market experience of different types of worker differs markedly. Some workers, typically those with university-level qualifications, have higher wages and greater job security than non-graduates (ONS (2017*a*)). The pandemic has highlighted this disparity, as lower paid workers with lower qualifications were more likely to be in key occupations and at higher risk from the virus (Gustafsson and McCurdy (2020)). Second, the distribution of graduates across occupations is complex, with over one third of graduates employed in "non-graduate" occupations (ONS (2017*a*)). And third, there is substantial movement of workers between jobs and between sectors, with most hires coming from workers who are already employed rather than from the unemployed (ONS (2017*c*)).[3]

Reflecting these features, our model distinguishes between workers with higher qualifications, who we identify as graduates, and workers with lower qualifications. We also distinguish between "high productivity" and "low productivity" firms; as we document below, high productivity firms pay higher wages and offer greater job security. We assume that only graduates can work in high productivity firms, while all workers can work at low productivity firms.[4] [5] As we describe below, the UK labour

[1]The Bank of England projects a 9% unemployment rate (BoE (2020*a*)). The Office for Budgetary Responsibility projects 11.9% (OBR (2020)).

[2]Faccini et al. (2013) analyse this type of model for the UK.

[3]Only 28% of new hires in groups 1)-3) in the UK Standard Occupational Classification (SOC) (ONS (2009)): "Managers, directors & senior officials", "Professional occupations" and "Associate professional & technical", come from the unemployed. And only 46% of workers with lower qualifications into groups 4)-9) of the SOC come from the unemployed.

[4]Two sector DSGE models with labour market frictions have been developed to address policy issues in less developed countries, where the distinction between the "formal" and "informal" sectors is important (eg Castillo and Montoro (2012*b*) and Mattesini and Rossi (2009).). In contrast to our model, these models typically assume that only unemployed workers can be hired by any firm. They also differ from our model by assuming either no mobility (so only high qualification workers can work at high productivity firms and only low qualification workers can work at low productivity firms) or complete mobility (all workers are identical and can do any job).

[5]Our model has similarities with the literature on "good jobs and bad jobs" (eg Gertler et al. (2020*a*) and Faccini and Melosi (2020)). In these models, both employed and unemployed workers can be hired. The productivity of a job match is random and so low productivity job matches can arise even though workers and firms are identical. In our model, "bad matches" are not random; rather they arise when high qualification workers are employed by low productivity firms.

market is characterised by flows of workers moving between high productivity jobs, moving between low productivity jobs, moving from low productivity jobs to high productivity jobs, and vice versa. There are also flows of workers from unemployment to and from high and low productivity jobs. In our model, we generate worker flows to match these data through job search. New hires into high productivity jobs can be from unemployment, from another high productivity job or from a low productivity job. New hires of lower qualification workers into low productivity jobs can come from unemployment or from another low productivity job. New hires of higher qualification workers into low productivity jobs can come from unemployment, from another low productivity job or from a high productivity job. In addition, since all jobs can end, there are also flows of high and low qualification workers out from low productivity firms into unemployment and flows of high qualification workers from high productivity firms into unemployment.

We model the impact of COVID-19 on the UK labour market as a series of simultaneous adverse shocks. Baqaee and Farhi (2020) use a similar approach, modelling the impact of the pandemic on the US as an "omnibus of various supply and demand shocks". Related work includes Maria del Rio-Chanona et al. (2020), who investgate how COVID-19 has led to the adverse supply and demand shocks in the US and Fornaro and Wolf (2020) and Guerrieri et al. (2020), who conceptualise the transmission of adverse supply shocks into adverse demand shocks. Other models (eg Eichenbaum et al. (2020)) incorporate simple Susceptible-Infectious-Recovered epidemiological processes into DSGE models, to analyse how households may have reduced labour supply and consumption demand in response to COVID-19, generating a large, persistent recession. Mihailov (2020) incorporates these effects into the DSGE model of Galí et al. (2020) to estimate the impact of COVID-19. Our model has similarities with this approach, but has a greater emphasis on the labour market experience of different types of workers, on labour market frictions and on wage bargaining.

We classify the shocks in our simulation as being either aggregate supply or aggregate demand shocks. Aggregate supply shocks comprise shocks that reduce the workforce due to workers being in self-isolation or sick with COVID-19; shocks that increase job destruction;[6] shocks that reduce productivity, due to employees working from home or being furloughed as part of the Job Retention Scheme;[7] and shocks to wages, due to the state paying a proportion of wages as part of the JRS. Reflecting UK evidence on the incidence of these shocks in different sectors, the severity of these shocks differs between high- and low productivity jobs. Aggregate demand shocks comprise shocks that rise from households reducing expenditure in response to the pandemic, and having reduced opportunities to spend;[8] and shocks to the interest rate due to the monetary policy response to the crisis.[9] We also model a shock to the composition of aggregate demand to capture the especially large demand fall in the hospitality, leisure and related sectors.[10]

Simulations of our model broadly match other predictions of the economic impact of the pandemic at the aggregate level. In our baseline scenario, output falls sharply but then recovers relatively quickly, returning to pre-pandemic levels by mid-2021. Unemployment increases to 3.0 million workers, an unemployment rate of 8.7%; unemployment recovers slowly and does not return to pre-pandemic levels until

[6]The impact of these shocks is modelled for the US by Arbex et al. (2020).

[7]Similar schemes are in place Germany, France, Switzerland, the Netherlands and other countries, based on the German "Kurzarbeit" model, (Rothwell and Van Drie (2020)).

[8]This has been partly offset by increases in Government expenditure; for example, expenditure on health and social care increased by nearly 50% in the early stages of the pandemic. These were financed by large increases in borrowing, around £50 billion per month.

[9]The Bank of England has responded strongly to the pandemic, announcing renewed Quantitative Easing purchases that increased the total stock of asset purchases to £745 billion by the end of June. It also undertook long-term lending to banks at low interest rates, with the intention that this results in increased low-rate credit flows to firms, and increased it's loan facility for the UK Treasury.

[10]Faria-e Castro (2020) models this effect using a shock to the marginal utility from consumption of the output of the service sector.

2022. Our baseline scenario projects deflation in 2020, followed by several years of above-target inflation during the recovery from the pandemic. We find that real wages fall by 0.9%.

We find that the COVID-19 pandemic has exacerbated structural differences in the UK labour market as the pandemic has very different impacts on graduates compared to non-graduates. We project a large surge in job losses, an additional 1.2 million job losses for non-graduates and an additional 400,000 job losses for graduates.[11] As a result, the unemployment rate of non-graduates rises to 10.1% compared to 6.8% for graduates. The real wage of non-graduates falls more than the real wage of graduates. These effects unwind slowly over time; the structure of employment does not return to pre-pandemic levels until 2024. The more severe impact of the pandemic on non-graduates arises because the more difficult labour market environment for these workers is compounded by the differential impact of the pandemic, as sectors that were especially severely impacted by the crisis, such as tourism and hospitality, employ a larger proportion of lower qualification workers. We find that these two factors have roughly equal importance in explaining the impact of the pandemic on less highly qualified workers.

Research into an ongoing event of the scale and rarity of the COVID-19 pandemic must be treated with caution. In order to analyse the impact of the pandemic, this paper makes a series of strong assumptions. First, our model does not allow for uncertainty. Second, our model tracks 11 distinct labour market flows. This enables the model to capture some of the richness of the UK labour market, but also makes the model complex. This complexity comes at a cost, as our model does not analyse movements of workers in and out of self-employment or in and out of the labour force. Third, we assume that the pandemic does not affect the steady-state of the UK economy; and that the pandemic does not change structural relationships. Fourth, we assume it is appropriate to use a linearised version of the model,[12] even though the pandemic moves the economy some distance away from the steady-state.[13] Further research that address the impact of the pandemic using alternative approaches would be useful.

3.2 The Model

3.2.1 Overview

The economy is composed of households, wholesale firms, retail firms, the government and the Central Bank. Households are composed of two types of worker: graduates and non-graduates. There are two types of goods and two types of firms. High productivity wholesale firms use graduates to produce high productivity wholesale goods. They sell these to high productivity retail firms who use them to produce high productivity retail goods, which they sell to households. Low productivity wholesale firms use graduates and non-graduates to produce low productivity wholesale goods. They sell these to low productivity retail firms who use them to produce low productivity retail goods, which are sold to households. Wholesale goods markets are competitive but retail goods markets are imperfectly competitive. The government collects taxes and purchases retail goods. The Central Bank sets the interest rate on the financial asset, which households use to smooth consumption over time.

[11] This is consistent with evidence in Tomlinson (2020), who finds that job losses in 2020Q2 were concentrated in areas such as Hospitality, Retail and Construction, with high proportions of employment of lower qualification workers. This is partly offset by an increase in employment in the Health and Care sectors. By contrast, job losses in sectors with higher concentrations of more highly qualified workers, such as Finance and Insurance and Public Administration are 5-6 times lower.

[12] Our use of a linearisation is pragmatic. Our model comprises over 60 relationships, many of which are nonlinear. Solving such a large nonlinear model is computationally impractical. Using a second-order expansion of such a large model is also impractical.

[13] Subjecting our model to the large scale shocks that are required to mimic the impact of the pandemic puts our simulations under stress; we find that values of vacancies and related labour market variables are highly volatile in the early phase of the pandemic, as firms first cease hiring in 2020Q2-Q3 and then seek to rebuild their workforce once recovery from the crisis begins.

At the beginning of each period, workers search for jobs and vacancies are posted by wholesale firms without a productive job match. This results in new job matches being formed, which become productive in the same period. Next, wages are set and wholesale goods are produced. Then, job separation occurs. Some employer-worker job matches survive and continue into the next period; other matches break down. Separated workers enter the next period as unemployed and begin search for a new job then.[14]

3.2.2 The Labour Market

There are two types of workers: graduates L^g and non-graduates L^{ng}. In the pre-pandemic period $L^g + L^{ng} = L$, where we use $L = 1$ as a normalisation. All graduates are identical and all non-graduates are identical. During the pandemic, the number of graduates is $L_t^g = L^g e^{\varepsilon_t^g}$ and the number of non-graduates is $L_t^{ng} = L^{ng} e^{\varepsilon_t^{ng}}$, where ε_t^g and ε_t^{ng} are shocks that capture the impact of the pandemic on the workforce such as illness and hospitalisation due to coronavirus infection, and self-isolation.[15]

Graduates can be employed by high or low productivity wholesale firms, but non-graduates can only be employed by low productivity wholesale firms. In any period, u_t^g graduates are unemployed, $n_t^{l,g}$ are employed by low productivity firms and $n_t^{h,g}$ are employed by high productivity firms, so

$$L_t^g = u_t^g + n_t^{l,g} + n_t^{h,g} \tag{3.1}$$

Similarly, in any period, u_t^{ng} non-graduates are unemployed and $n_t^{l,ng}$ are employed by low productivity firms, so

$$L_t^{ng} = u_t^{ng} + n_t^{l,ng} \tag{3.2}$$

Following production, job separation occurs, at rates τ_t^h and τ_t^l for high and low productivity firms respectively. We assume that $\tau_t^l = \tau^l e^{\varepsilon_t^{\tau^l}}$ and $\tau_t^h = \tau^h e^{\varepsilon_t^{\tau^h}}$, $\tau^l > \tau^h$, where $\varepsilon_t^{\tau^l}$ and $\varepsilon_t^{\tau^h}$ are shocks to the rate of job destruction. The shocks will capture the wave of job losses induced by the pandemic.

We generate worker flows that match UK data through job search. All unemployed workers and all employed workers search for jobs. Search for a job offered by a high productivity firm comes from unemployed graduates, graduates employed by low productivity firms and from graduates employed by another high productivity firm. Search for jobs at high productivity firms is

$$s_t^h = s_t^{h,g,u} + s_t^{h,g,l} + s_t^{h,g,h} \tag{3.3}$$

$s_t^{h,g,u} = \zeta^{h,g,u} u_t^g$ is search for high productivity jobs by unemployed graduates, who each search with intensity $\zeta^{h,g,u}$. $s_t^{h,g,l} = \zeta^{h,g,l} n_t^{l,g}$ is search by graduates employed by low productivity firms, who each search for jobs at high productivity firms with intensity $\zeta^{h,g,l}$. And $s_t^{h,g,h} = \zeta^{h,g,h} n_t^{h,g}$ is search by graduates employed by high productivity firms, who each search with intensity $\zeta^{h,g,h}$.

Search for a job offered by a low productivity firm comes from unemployed graduates and non-graduates, from non-graduates employed by another low productivity firm, from graduates employed by another low productivity firm, and from graduates employed by high productivity firms. So search for jobs at low productivity firms is

$$s_t^l = s_t^{l,ng,u} + s_t^{l,ng,l} + s_t^{l,g,u} + s_t^{l,g,h} + s_t^{l,g,l} \tag{3.4}$$

[14]The Job Retention Scheme creates three choices for a firm: to continue a job match, to terminate it or to use a furlough. The option of a furlough adds an additional layer of complexity to the analysis of endogenous job destruction. This is beyond the scope of this paper, so we assume job destruction is exogenous.

[15]The shocks to the number of graduates and non-graduates due to the pandemic reflects the change in the size of the labour force from workers transitioning into economic inactivity. Since the model does not include the economically inactive, the shock reflects the impact of the pandemic on the labour force participation.

$s_t^{l,ng,u} = \zeta^{l,ng,u} u_t^{ng}$ and $s_t^{l,g,u} = \zeta^{l,g,u} u_t^g$ are search for low productivity jobs by unemployed graduates and non-graduates respectively, who search with intensity $\zeta^{l,ng,u}$ and $\zeta^{l,g,u}$. $s_t^{l,ng,l} = \zeta^{l,ng,l} n_t^{l,ng}$, $s_t^{l,g,h} = \zeta^{l,g,h} n_t^{h,g}$, and $s_t^{l,g,l} = \zeta^{l,g,l} n_t^{l,g}$ are search by non-graduates employed by low productivity firms, search by graduates employed by high productivity firms and search by graduates employed by low productivity firms, who search for jobs with intensity $\zeta^{l,ng,l}$, $\zeta^{l,g,h}$ and $\zeta^{l,g,l}$ respectively. Job search and worker flows are summarised in Fig 3.1.

We assume that workers search with fixed intensity. This is in line with most of the recent literature, including Faccini and Melosi (2020), Moscarini and Postel-Vinay (2018*b*) and Moscarini and Postel-Vinay (2017), who model search by employed and unemployed workers in a one-sector model with identical firms and workers. Leduc and Liu (2020) model variable search intensity in a one-sector model where only unemployed workers can search for jobs and Gertler et al. (2020*a*) analyse a one-sector model in which the productivity of a job match is randomly assigned to be high or low. The unemployed and workers in high productivity jobs search with a fixed intensity, but workers looking to move up from a low productivity match to a high productivity match search with varying intensity. In total, we use labour market search to generate 11 distinct types of worker flows in our two-sector model. This complexity makes consideration of variable search intensity impractical.

High productivity wholesale firms post vacancies v_t^h. Only high qualification workers can be matched to vacancies posted by high productivity firms. High productivity job matches are formed with the matching function

$$h_t^h = m^h (v_t^h)^{\alpha_h} (s_t^h)^{1-\alpha_h} \tag{3.5}$$

where m^h is the high productivity matching efficiency and α_h and $1-\alpha_h$ are elasticities. Job matches are formed with unemployed graduates, graduates currently employed in low and high productivity firms, so $h_t^h = h_t^{h,g,u} + h_t^{h,g,l} + h_t^{h,g,h}$, where $h_t^{h,g,u}$ is the number of unemployed graduates hired by high productivity firms, $h_t^{h,g,l}$ is the number of graduates employed in low productivity firms who find a new job at a high productivity firm and $h_t^{h,g,h}$ is the number of graduates employed in other high productivity firms who find a new job at a high productivity firm. We assume that the proportion of hires from each group depends on their relative search, so $h_t^{h,g,u} = \frac{s_t^{h,g,u}}{s_t^h} h_t^h$, $h_t^{h,g,l} = \frac{s_t^{h,g,l}}{s_t^h} h_t^h$, and $h_t^{h,g,h} = \frac{s_t^{h,g,h}}{s_t^h} h_t^h$.

Labour market tightness for high productivity firms is

$$\theta_t^h = \frac{v_t^h}{s_t^h} \tag{3.6}$$

so high productivity firms fill their vacancies at rate $q_t^h = \frac{h_t^h}{v_t^h}$ and the rate at which high qualification workers are matched with a vacancy at a high productivity firm, per unit of search, is $f_t^h = \frac{h_t^h}{s_t^h}$. The job finding rate of unemployed graduates seeking work in high productivity firms is[16] $f_t^{h,g,u} = \frac{h_t^{h,g,u}}{u_t^g} = \zeta^{h,g,u} f_t^h$. Similarly, the job finding rates of graduates currently employed in low or high productivity firms seeking work in high productivity firms are $f_t^{h,g,l} = \frac{h_t^{h,g,l}}{n_t^{l,g}} = \zeta^{h,g,l} f_t^h$ and $f_t^{h,g,h} = \frac{h_t^{h,g,h}}{n_t^{h,g}} = \zeta^{h,g,h} f_t^h$ respectively.

Low productivity wholesale firms post vacancies v_t^l. Low productivity job matches are formed with the matching function

$$h_t^l = m^l (v_t^l)^{\alpha_l} (s_t^l)^{1-\alpha_l} \tag{3.7}$$

and m^l is the high productivity matching efficiency and α_l and $1-\alpha_l$ are elasticities. We again assume that the proportion of hires from each source of hires depends on their relative search. The number of unemployed non-graduates hired by low productivity firms is $h_t^{l,ng,u} = \frac{s_t^{l,ng,u}}{s_t^l} h_t^l$ and the number of

[16]Since $f_t^{h,g,u} = \frac{h_t^{h,g,u}}{u_t^g} = \frac{s_t^{h,g,u}}{s_t^h} \frac{h_t^h}{u_t^g} = \frac{s_t^{h,g,u}}{u_t^g} f_t^h = \zeta^{h,g,u} f_t^h$

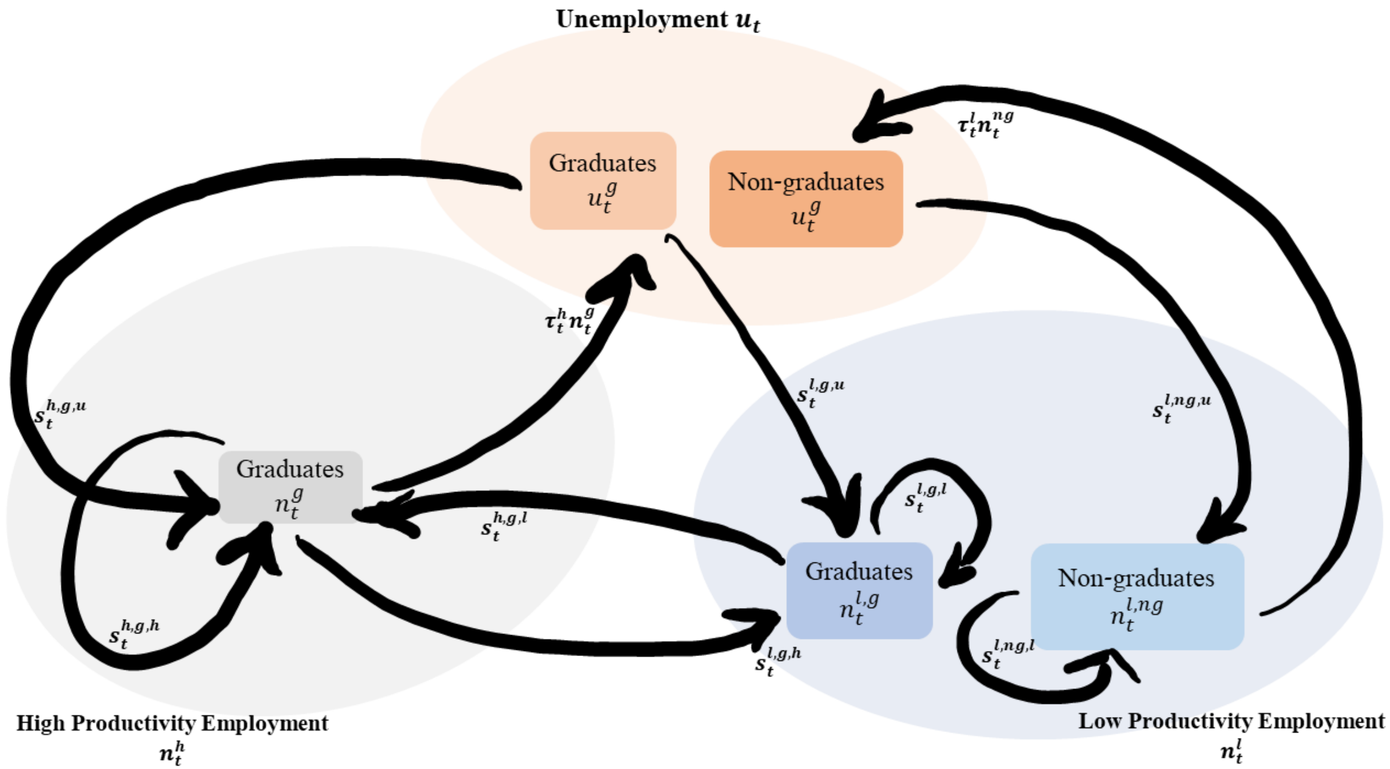

Figure 3.1: UK Graduate and Non-graduate Labour Market Flows

The figure shows 10 different movements of graduates and non-graduates in the UK labour market identified in the model.The data shows that graduates search for non-graduate jobs as a stepping stone to, or when unable to find graduate employment, when facing redundancy or retirement, to meet a demand in the market, due to illness, disability or full-time education, and so on. Also, within-sector job search may be due to idiosyncratic reasons, for example, when facing difficulties at work, for proximity workplace to home, relocation, etc.

unemployed graduates hired by low productivity firms is $h_t^{l,g,u} = \frac{s_t^{l,g,u}}{s_t^l} h_t^l$. The number of non-graduates employed in low productivity jobs who find jobs at other low productivity firms is $h_t^{l,ng,l} = \frac{s_t^{l,ng,l}}{s_t^l} h_t^l$, and the number of graduates employed by high productivity firms who are hired by low productivity firms is $h_t^{l,g,h} = \frac{s_t^{l,g,h}}{s_t^l} h_t^l$. Low productivity market tightness is

$$\theta_t^l = \frac{v_t^l}{s_t^l} \tag{3.8}$$

so low productivity firms fill their vacancies at rate $q_t^l = \frac{h_t^l}{v_t^l}$ and the rate at which workers are matched with a vacancy at a low productivity firm is $f_t^l = \frac{m_t^l}{s_t^l}$. The job finding rates of unemployed graduates and non-graduates seeking work in low productivity firms are $f_t^{l,ng,u} = \frac{h_t^{l,ng,u}}{u_t^{ng}} = \zeta^{l,ng,u} f_t^l$ and $f_t^{l,g,u} = \frac{h_t^{l,g,u}}{u_t^g} = \zeta^{l,g,u} f_t^l$ respectively. And the job finding rates of non-graduates employed in low productivity firms and graduates employed in high productivity firms seeking work in low productivity firms are $f_t^{l,ng,l} = \frac{h_t^{l,ng,l}}{n_t^{l,ng}} = \zeta^{l,ng,l} f_t^l$ and $f_t^{l,g,h} = \frac{h_t^{l,g,h}}{n_t^{h,g}} = \zeta^{l,g,h} f_t^l$ respectively.

3.2.3 Households

Household members collectively derive utility from consumption. The household utility function is

$$H_t = E_t \sum_{k=0}^{\infty} \beta e^{\varepsilon_{t+k}^d} \frac{C_{t+k}^{1-\eta}}{1-\eta} \tag{3.9}$$

where C is consumption, η is the intertemporal elasticity of consumption and e^{ε^d} is a preference shock. We assume that $\varepsilon^d < 0$ during the pandemic and its aftermath.

As discussed below, all graduates in high productivity jobs earn the same real wage, w_t^h and all workers, graduates and non-graduates, in low productivity jobs earn the same real wage, w_t^l. The budget constraint of the household is

$$P_t w_t^l n_t^l + P_t w_t^h n_t^{h,g} + P_t b u_t + B_{t-1} + \Pi_t - T_t = P_t C_t + P_t^b B_t \tag{3.10}$$

where P is the consumption price index, $u_t = u_t^{ng} + u_t^g$ is the number of unemployed workers, $n_t^l = n_t^{l,g} + n_t^{l,ng}$ is the number of workers employed by low productivity firms, b is the real opportunity cost of employment, comprising the value of leisure and unemployment benefit, $P^b = \frac{1}{1+i}$ is the nominal price of bonds, Π is the profit the household receives for the ownership of firms and T_t is a lump-sum tax levied on the household by the government.

The household chooses consumption and bond purchases to maximise utility subject to their budget constraint. The optimality condition for consumption and bonds gives the Euler equation

$$C_t^{-\eta} = \beta e^{\varepsilon_t^d} E_t C_{t+1}^{-\eta} \frac{1+i_t}{1+E_t \pi_{t+1}} \tag{3.11}$$

The real interest rate $r_t = \frac{1+i_t}{1+E_t\pi_{t+1}}$, so equation (4.12) implies that the stochastic discount factor is

$$E_t \beta_{t,t+1} = \beta e^{\varepsilon_t^d} \frac{E_t C_{t+1}^{-\eta}}{C_t^{-\eta}} \tag{3.12}$$

The household derives utility from consuming both high productivity retail goods and low productivity retail goods. We assume

$$C_t = \left[(\Gamma_t^h)^{\frac{1}{\nu}}(C_t^h)^{\frac{\nu-1}{\nu}} + (1-\Gamma_t^h)^{\frac{1}{\nu}}(C_t^l)^{\frac{\nu-1}{\nu}}\right]^{\frac{1}{\nu-1}} \tag{3.13}$$

where C^h is consumption of high productivity retail goods, C^l is consumption of low productivity retail goods and ν is the elasticity of substitution between them. Γ_t^h is the proportion of household consumption that is of high productivity retail goods and $\Gamma_t^h = \Gamma_h e^{\varepsilon^{\Gamma_t^h}}$, where $\varepsilon^{\Gamma_t^h}$ is a shock to the preference for high productivity retail goods relative to low productivity retail goods. We use this shock in modelling the impact of the pandemic on the demand for different types of goods. The implied price index is

$$P_t = \left[\Gamma_t^h(P_t^h)^{1-\nu} + (1-\Gamma_t^h)(P_t^l)^{1-\nu}\right]^{\frac{1}{1-\nu}} \tag{3.14}$$

where P_t^h is the price index for high productivity retail goods and P_t^l is the price index for low productivity retail goods. The demand for high productivity and low productivity retail goods is

$$C_t^h = \Gamma_t^h\left(\frac{P_t^h}{P_t}\right)^{-\nu} C_t \tag{3.15}$$

and

$$C_t^l = (1-\Gamma_t^h)\left(\frac{P_t^l}{P_t}\right)^{-\nu} C_t \tag{3.16}$$

Household consumption of high productivity retail goods is a composite of individual high productivity retail goods defined by $C_t^h = (\int_0^1 (C_{jt}^h)^{\frac{\nu^h-1}{\nu^h}} dj)^{\frac{\nu^h}{\nu^h-1}}$, where C_j^h is household consumption of high productivity retail good j and ν^h is the elasticity of substitution between high productivity goods. The price index for high productivity retail goods is $P_t^h = (\int_0^1 (P_{jt}^h)^{(1-\nu^h)} dj)^{\frac{1}{1-\nu^h}}$ where P_j^h is the price of high productivity retail good j.

Similarly, household consumption of low productivity retail goods is a composite of individual low productivity retail goods defined by $C_t^l = (\int_0^1 (C_{jt}^l)^{\frac{\nu^l-1}{\nu^l}} dj)^{\frac{\nu^l}{\nu^l-1}}$, where C_j^l is household consumption of low productivity retail good j and ν^l is the elasticity of substitution between low productivity goods. The corresponding price index is $P_t^l = (\int_0^1 (P_{jt}^l)^{(1-\nu^l)} dj)^{\frac{1}{1-\nu^l}}$ where P_j^l is the price of low productivity retail good j.

Households purchase high productivity retail good j from the retail firm in the high productivity retail sector that sells this good. Household demand is

$$C_{jt}^h = \left(\frac{P_{jt}^h}{P_t^h}\right)^{-\nu^h} C_t^h \tag{3.17}$$

Similarly, households purchase low productivity retail good j from the retail firm in the low productivity retail sector that sells this good. Household demand for this good is

$$C_{jt}^l = \left(\frac{P_{jt}^l}{P_t^l}\right)^{-\nu^l} C_t^l \tag{3.18}$$

3.2.4 The Central Bank and Aggregate Demand

Aggregate demand equals aggregate output[17]

$$Y_t = C_t \tag{3.19}$$

[17] An alternative formulation of this $Y_t = C_t + \gamma^h v_t^h + \gamma^l v_t^l$, where γ^h and γ^l are the costs of posting a vacancy for high and low productivity firms, respectively. In our simulations, the increased volatility of vacancies in 2020Q2 and 202Q3 distorts this relationship, leading to unreliable results.

We assume that the Central Bank sets the interest rate using the simple Taylor rule

$$i_t = \bar{i} + \phi_\pi \pi_t + \phi_y \hat{y}_t + \varepsilon_t^i \tag{3.20}$$

where $\hat{y}$ is the output gap and ε_t^i is a monetary policy shock.

3.2.5 Wholesale Firms

High Productivity Wholesale Firms

All high productivity wholesale firms are competitive and identical. There is no rigidity in wholesale prices, so all high productivity wholesale firms set the same price. The objective function of the high productivity wholesale firm is

$$J_t^h = E_t \sum_{k=0}^{\infty} \beta^{t+k} \frac{\Lambda_{t+k}}{\Lambda_t} \Big\{ \frac{P_t^{h,W}}{P_t^h} Y_{t+k}^{h,W} - w_{t+k}^h n_{t+k}^h - \gamma^h v_{t+k}^h \Big\} \tag{3.21}$$

where $Y^{h,W}$ is output, $P^{h,W}$ is the price of the output of high productivity wholesale firms, P^h is the price of the output of high productivity retail firms and γ^h is the cost of posting a vacancy for high productivity firms. The production function is

$$Y_t^{h,W} = A_t^h n_t^{h,g} \tag{3.22}$$

where $A_t^h = A^h e^{\varepsilon_t^{s^h}}$, where $\varepsilon_t^{s^h}$ is a shock to the productivity of workers at high productivity firms. $\varepsilon_t^{s^h} < 0$ during the pandemic, as some employed workers will be furloughed under the Job Retention Scheme and others will be working from home, where they are less productive. Considering the evolution of employment, $n_t^{h,g}$ graduates are employed and used in production in period t. Following production, $\tau_t^h n_t^{h,g}$ workers are separated and become unemployed. At the start of period $t+1$, $f_{t+1}^{h,g,h} n_t^{h,g}$ workers move to other high productivity firms and $f_{t+1}^{l,g,h} n_t^{h,g}$ move to a low productivity firm. The firm posts v_{t+1}^h vacancies and recruits $q_{t+1}^h v_{t+1}^h$ new graduates. Defining $\rho_t^h = 1 - \tau_t^h - f_{t+1}^{h,g,h} - f_{t+1}^{l,g,h}$, the evolution of employment for the high productivity wholesale firm is therefore

$$n_{t+1}^h = \rho_t^h n_t^h + q_{t+1}^h v_{t+1}^h \tag{3.23}$$

The firm chooses the number of vacancies to post to maximise (3.21) subject to (3.22) and (3.23). The optimality condition is

$$\frac{\partial J_{t+1}^h}{\partial v_{t+1}^h} = -\gamma^h + E_t q_{t+1}^h \frac{\partial J_{t+1}^h}{\partial n_{t+1}^h} = 0 \tag{3.24}$$

where $\frac{\partial J_t^h}{\partial n_t^h} = \frac{A_t^h}{\mu^h} - w_t^h + \rho_t^h E_t \beta_{t,t+1} \frac{\partial J_{t+1}^h}{\partial n_{t+1}^h}$ and where $\mu^h = \frac{P_t^h}{P_t^{h,W}}$. Noting that (3.24) implies $\frac{\partial J_{t+1}^h}{\partial n_{t+1}^h} = \frac{\gamma^h}{E_t q_{t+1}^h}$, and so $\frac{\partial J_t^h}{\partial n_t^h} = \frac{A_t^h}{\mu^h} - w_t^h + \rho_t^h E_t \beta_{t,t+1} \frac{\gamma}{q_{t+1}^h}$, the optimality condition implies

$$\frac{A_t^h}{\mu^h} = w_t^h + \lambda_t^h \tag{3.25}$$

where the high productivity sector marginal hiring cost $\lambda_t^h = \gamma^h(\frac{1}{q_t^h} - \rho_t^h E_t \beta_{t,t+1} \frac{1}{q_{t+1}^h})$. Given the assumption that high productivity wholesale firms are in perfect competition, the job creation condition in (3.25) implies that the marginal revenue derived from an additional graduate worker $\frac{A_t^h}{\mu^h}$ is equal to the marginal cost, where the marginal cost is the sum of the wage and the marginal hiring cost.

Low Productivity Wholesale Firms

Low productivity wholesale firms employ both graduates and non-graduates, so employment is $n_t^l = n_t^{l,g} + n_t^{l,ng}$. Due to a legal or fairness constraint, all workers employed at the firm must be paid the same wage w_t^l. The objective function of low productivity wholesale firms is

$$J_t^l = \sum_{k=0}^{\infty} \beta^{t+k} \frac{\Lambda_{t+k}}{\Lambda_t} \left\{ \frac{P_t^{l,W}}{P_t^l} Y_{t+k}^{l,W} - w_{t+k}^l n_{t+k}^l - \gamma^l v_{t+k}^l \right\} \tag{3.26}$$

where $Y^{l,W}$ is output, $P^{l,W}$ is the price of the output of low productivity wholesale firms, P^l is the price of the output of low productivity retail firms and γ^l is the cost of posting a vacancy for low productivity firms. The production function is

$$Y_t^{l,W} = A_t^l n_t^l \tag{3.27}$$

where $A_t^l = A^l e^{\varepsilon_t^{s^l}}$, and $\varepsilon_t^{s^l}$ is a shock to the productivity of workers at low productivity firms; we assume that graduates and non-graduates are equally productive in the low productivity employment. $\varepsilon_t^{s^l} < 0$ during the pandemic, due to some employed workers being furloughed and others working from home.

The evolution of employment at low productivity firms reflect the different evolutions of employment of graduates and non-graduates. Considering graduate employment, $n_t^{l,g}$ workers are employed and used in production in period t. Following this, $\tau_t^l n_t^{l,g}$ workers are separated. In period $t+1$, $f_{t+1}^{h,g,l} n_t^{l,g}$ workers move to high productivity firms and $f_{t+1}^{l,g,l} n_t^{l,g}$ workers move to other low productivity firms. The firm posts v_{t+1}^l vacancies and recruits $q_{t+1}^{l,g} v_{t+1}^l$ new graduates. Defining $\rho_t^{l,g} = 1 - \tau_t^l - f_{t+1}^{h,g,l} - f_{t+1}^{l,g,l}$, the evolution of graduates at the representative low productivity wholesale firm is therefore

$$n_{t+1}^{l,g} = \rho_t^{l,g} n_t^{l,g} + q_{t+1}^{l,g} v_{t+1}^l \tag{3.28}$$

Following similar arguments, the evolution of non-graduate employment at the representative low productivity wholesale firm is

$$n_{t+1}^{l,ng} = \rho_t^{l,ng} n_t^{l,ng} + q_{t+1}^{l,ng} v_{t+1}^l \tag{3.29}$$

where $\rho_t^{l,ng} = 1 - \tau_t^l - f_{t+1}^{l,ng,l}$. The evolution of employment at the firm is therefore

$$n_{t+1}^l = \left\{ \rho_t^{l,g} n_t^{l,g} + \rho_t^{l,ng} n_t^{l,ng} \right\} + (q_t^{l,g} + q_t^{l,ng}) v_t^l \tag{3.30}$$

Defining $\delta_{jt}^{l,g} = \frac{n_t^{l,g}}{n_t^l}$ as the proportion of the firm's workforce that are graduates and $q_t^l = q_t^{l,g} + q_t^{l,ng}$, we obtain

$$n_{t+1}^l = \rho_t^l n_t^l + q_t^l v_t^l \tag{3.31}$$

where $\rho_t^l = \rho_t^{l,g} \delta_t^{l,g} + \rho_t^{l,ng} (1 - \delta_t^{l,g})$.

The firm chooses the number of vacancies to post to maximise(3.26) subject to (3.27) and (3.31). The optimality condition is

$$\frac{\partial J_{t+1}^l}{\partial v_{t+1}^l} = -\gamma^l + E_t q_{t+1}^l \frac{\partial J_{t+1}^l}{\partial n_{t+1}^l} = 0 \tag{3.32}$$

where $\frac{\partial J_t^l}{\partial n_t^l} = \frac{A_t^l}{\mu^l} - w_t^l + \rho_t^l E_t \beta_{t,t+1} \frac{\partial J_{t+1}^l}{\partial n_{t+1}^l}$ and $\mu^l = \frac{P_t^l}{P_t^{l,W}}$. Noting that (3.32) implies $\frac{\partial J_{t+1}^l}{\partial n_{t+1}^l} = \frac{\gamma^l}{E_t q_{t+1}^l}$, and so $\frac{\partial J_t^l}{\partial n_t^l} = \frac{A_t^l}{\mu^l} - w_t^l + \rho_t^l E_t \beta_{t,t+1} \frac{\gamma^l}{q_{t+1}^l}$, the optimality condition implies

$$\frac{A_t^l}{\mu^l} = w_t^l + \lambda_t^l \tag{3.33}$$

where $\lambda_t^l = \gamma^l(\frac{1}{q_t^l} - \rho_t^l E_t \beta_{t,t+1} \frac{1}{q_{t+1}^l})$.

3.2.6 Wage Determination

In this model, wages are determined through wage bargaining, with real wage rigidity, where we model real wage rigidity following Faia (2008) and Krause and Lubik (2007).[18] We also model the impact of a temporary wage subsidy due to the Job Retention Scheme, which we treat as a shock. The wage paid by high productivity firms is

$$w_t^h = \{\varphi^h w^h + (1-\varphi^h) w_t^{b,h}\} e^{-\varepsilon_t^{w^h}} \tag{3.34}$$

where $w_t^{b,h}$ is the wage implied by bargaining, w^h is the steady-state value of this wage, φ^h captures real wage rigidity and ε^{w^h} is the wage subsidy. The wage received by workers employed in high productivity firms is

$$w_t^{h,w} = \varphi^h w^h + (1-\varphi^h) w_t^{b,h} \tag{3.35}$$

The bargained wage is chosen to maximise

$$S_t = (S_t^{h,g})^{\zeta^h} (F_t^h)^{1-\zeta^h} \tag{3.36}$$

where $S_t^{h,g}$ is the surplus to the household from an additional worker being employed in a high productivity firm, F_t^h is the surplus to the firm and ζ^h is the bargaining power of graduates in high productivity jobs. This gives the sharing rule

$$(1-\zeta^h) S_t^{h,g} = \zeta^h F_t^h \tag{3.37}$$

As we show in the Appendix, this results in

$$w_t^{b,h} = \zeta^h \left\{ \frac{P_t^{h,W}}{P_t^h} A_t^h + \gamma^h \zeta^{h,g,u} E_t \theta_{t+1}^h + \gamma^l \zeta^{l,g,u} E_t \theta_{t+1}^l \right\} + (1-\zeta^h) b \tag{3.38}$$

As shown in (3.38), market tightness in both sectors impact the high productivity sector bargained wage. This comes from the ability of graduates to fill either high or low productivity sector job positions. In the absence of the low productivity sector or mobility between sectors, graduates would be employed in the high productivity sector and unemployed otherwise; so (3.38) reflects that for one less unemployed graduate, the household receives value from an additional graduate employed in the high productivity sector $\zeta^{h,g,u} E_t \theta_{t+1}^h$, who also had the opportunity of employment in the low productivity sector $\zeta^{l,g,u} E_t \theta_{t+1}^l$.

The wage for high productivity wholesale firms is therefore determined by (3.34) and (3.38).

Using a similar notation, the wage paid by low productivity firms is

$$w_t^l = \{\varphi^l w^l + (1-\varphi^l) w_t^{b,l}\} e^{-\varepsilon_t^{w^l}} \tag{3.39}$$

and the wage received by workers employed in low productivity firms is

$$w_t^{l,w} = \varphi^l w^l + (1-\varphi^l) w_t^{b,l} \tag{3.40}$$

Graduates in low productivity employment have the same productivity as non-graduates, and for fairness

[18] A major weakness of the Mortensen-Pissarides search model is the inability of the model to match business cycle fluctuations in unemployment and vacancies. The standard search model predicts excess volatility in the real wage, and little employment response. This drawback is resolved by the introduction of wage rigidities into the model (see for example Pissarides (2009) and Shimer (2005) for discussion.). Given the number of shocks in our model, we assume that there is real wage rigidity, so that the volatility in the real wages does not suppress the employment response in the model. Our assumption of real wage rigidity is also consistent with the data on UK wages (see, for example, Babecky et al. (2010) and Holden and Wulfsberg (2009)).

and legal constraints, we assume that both types of worker in low productivity employment must be paid the same wage. However, a match with a non-graduate has a different value to a low productivity firm than a match with a graduate. This is because graduates can transition to high productivity employment, but non-graduates cannot, so the low productivity match with a graduate has a lower probability of contiunation than a match with a non-graduate. Therefore, we assume that wage bargaining only takes place between the firm and non-graduates. The bargained wage is determined by the sharing rule

$$(1-\zeta^l)S_t^{l,ng} = \zeta^l F_t^l \tag{3.41}$$

where $S_t^{l,ng}$ is the surplus to the household from an additional non-graduate being employed in a low productivity firm, F_t^l is the surplus to the firm and ζ^l is the bargaining power of non-graduates in the low productivity sector. This implies (see Appendix for details)

$$w_t^{b,l} = \zeta^l \left\{ \frac{P_t^{l,W}}{P_t^l} A_t^l + \gamma^l \zeta^{l,ng,u} E_t \beta_{t,t+1} \theta_{t+1}^l \right\} + (1-\zeta^l) b \tag{3.42}$$

In this case, there is no mobility between sectors for non-graduates. This means that the opportunity cost to the household for an unemployed non-graduate is an employed non-graduate earning a wage which is a function of their search intensity and the low productivity sector market tightness alone.

3.2.7 Retail Firms

High Productivity Retail Firms

High productivity retail firms produce differentiated high productivity retail goods, which they sell to households. High productivity retail firms face a downward sloping demand curve and determine the price of their output, acting as monopolistic competitors. High productivity retail firms purchase high productivity wholesale goods in a competitive market and transform these costlessly into a differentiated high productivity retail good.

The production function for the high productivity retail firm is

$$Y_t^h = Y_t^{h,W} \tag{3.43}$$

where $Y^{h,W}$ is the amount of high productivity wholesale goods purchased by the high productivity retail firm. High productivity sector retail firms can adjust their price in each period with probability $(1-\omega^h)$. In period t, they therefore choose their price, P_t^h, to maximise

$$E_t \sum_{k=0}^{\infty} (\omega^h)^k \left\{ \beta_{t,t+k} \left(\frac{P_t^h - P_{t+k}^{h,W}}{P_{t+k}^h} \right) Y_{t+k}^h \right\} \tag{3.44}$$

subject to

$$Y_t^h = \left(\frac{P_t^h}{P_t^h} \right)^{-\nu^h} Y_t^h \tag{3.45}$$

This gives the optimal price of the high productivity firm's finished good

$$\frac{P_t^{*h}}{P_t^h} = \mu(1-\beta\omega^h) E_t \sum_{k=0}^{\infty} (\omega^h)^k \beta_{t,t+k} mc_{t+k}^h \tag{3.46}$$

where $mc_{t+k}^h = \frac{P_t^{h,W}}{P_{t+k}^h}$ is the price of the high productivity intermediate good and $\mu^h = \frac{\nu^h}{\nu^h - 1}$ is the markup, high productivity retail firms set their price as a markup on their marginal cost.

High productivity retail firms that are unable to reset their price maintain their past optimal price indexed for inflation. This is consistent with the price setting rule

$$P_t^h = (1-\omega^h)P_t^{*h} + \omega^h \pi_{t-1}^h P_{t-1}^h \tag{3.47}$$

Taking the log deviation of (4.41) and the price setting rule around a zero inflation steady state gives the Phillips Curve for the high productivity sector

$$\pi_t^h = \frac{1}{1+\beta}\pi_{t-1}^h + \kappa^h \widehat{mc}_t^h + \frac{\beta}{1+\beta}\pi_{t+1}^h \tag{3.48}$$

where $\kappa^h = \frac{(1-\omega^h)(1-\beta\omega^h)}{\omega^h}$ is the slope.

Low productivity Retail Firms

Similarly, each low productivity retail firm produces a differentiated low productivity retail good, which it sells to households. Each low productivity retail firm faces a downward sloping demand curve and determines the price of their output, acting as a monopolistic competitor. Each low productivity retail firm purchases wholesale low productivity goods in a competitive market and transforms these costlessly into a differentiated low productivity retail good. Following the same argument as for high productivity retail firms, we obtain the price setting rule

$$P_t^l = (1-\omega^l)P_t^{*l} + \omega^l \pi_{t-1}^l P_{t-1}^l \tag{3.49}$$

where

$$\frac{P_t^{*l}}{P_t^l} = \mu(1-\omega^l\beta)E_t\sum_{k=0}^{\infty}(\omega^l)^k\beta_{t,t+k}mc_{t+k}^l \tag{3.50}$$

$mc_{t+k}^l = \frac{P_t^{l,W}}{P_{t+k}^l}$ is the price of the low productivity intermediate good and $\mu^l = \frac{\nu^l}{\nu^l-1}$. Taking the log deviation of (3.50) and (3.49) around a zero steady state gives the Phillips Curve

$$\pi_t^l = \frac{1}{1+\beta}\pi_{t-1}^l + \kappa^l \widehat{mc}_t^l + \frac{\beta}{1+\beta}\pi_{t+1}^l \tag{3.51}$$

where $\kappa^l = \frac{(1-\omega^l)(1-\beta\omega^l)}{\omega^l}$ is the slope.

3.3 Calibration

There are no similar studies of the UK labour market that distinguish between different types of workers. We therefore first construct a series of calibration targets. The most recent data on graduates in the UK labour market is for 2017 (ONS (2017*a*)). We assume that the UK labour market was in steady-state, relative to the impact of the pandemic, in that year. In 2017, 42% of the population aged 21-64 were graduates; so we set $L^g = 0.42$ and hence $L^{ng} = 0.58$. The unemployment rate of graduates in that year was 3%, so $\frac{u^g}{L^g} = 0.03$. This implies that unemployed graduates as a fraction of the labour force $u^g = \frac{u^g}{L^g}\frac{L^g}{L} = 0.013$. Since the workforce is normalised to 1, the unemployment rate is $u = u^g + u^{ng}$. The unemployment rate in 2017 was 4.3%, so $u^{ng} = 0.043 - 0.013 = 0.030$. Employment of graduates was $n^g = L^g - u^g = 0.407$. In 2017, 36.3% of employed graduates were in non-graduate occupations (ONS (2017*a*)). So we use $n^{h,g} = 0.407 * (1 - 0.363) = 0.26$ and $n^{l,g} = 0.407 * 0.363 = 0.15$ as calibration targets. Employment of non-graduates was $n^{l,ng} = L^{ng} - u^{ng} = 0.55$; we also target this value.

We target the wage in high productivity occupations relative to the wage in low productivity occupations. To construct this, we follow ONS practice and define a high productivity job as corresponding to groups 1)-3) in the UK Standard Occupational Classification (SOC) (ONS (2009)): "Managers, directors & senior officials", "Professional occupations" and "Associate professional & technical". We assume that high productivity firms only employ graduates in these occupations. We define a low productivity job as corresponding to groups 4)-9):[19] "Administrative & secretarial", "Skilled trades", "Caring, leisure & other services", "Sales & customer services, "Process, plant & machine operatives" and "Elementary occupations". We assume that all workers are able to occupy these roles. Using ONS data for 2017 on employment by occupation (ONS (2017*a*)) and weekly earnings by occupation (ONS (2017*b*)), we calculated that the average wage in high productivity occupations exceeds that in low productivity occupations by 190%. We target this in our calibrations.

For the rate of job destruction, we use data from the 2017 UK Labour Force Survey. This gives annual rates of job destruction for different occupations. We match these occupations to the UK SOC and use this to construct job survival rates for high and low productivity occupations. We obtain $\rho^h = 0.92$ and $\rho^l = 0.88$ as annual rates. In our calibration, we assume that a time period corresponds to one quarter. We use $\rho^h = 0.98$ and $\rho^l = 0.97$ as our quarterly calibration targets.

We construct calibration targets for job flows using data on flows of workers between employment and unemployment and between employment in different occupations. In steady-state, hires of graduates into the high productivity sector are $h^{h,g} = \rho^h n^{h,g} = 0.005$. These hires can come from workers in the high or low productivity sectors, or from unemployment. To calculate these flows, we used ONS data on job to job moves by skill level in 2017 (ONS (2017*c*)) to construct measures of job movements within the high productivity sector and of hires into the high productivity sector from the low productivity sector. We also combined data on total hires from unemployment (ONS (2020*c*)) with estimates of the percentage of hires from unemployment that went to the high productivity sector (ONS (2016*a*))[20] to construct a measure of hires into the high productivity sector from unemployment. This gave the relative sizes of the various flows into the high productivity sector: 28% of hires by high productivity firms came from unemployed graduates, 55% were from workers employed at other high productivity firms and 17% were hired from low productivity firms.

Using a similar approach, the number of graduates hired into the low productivity sector is $h^{l,g} = \rho^l n^{l,g} = 0.004$. These hires can come from workers in the high or low productivity sectors, or from unemployment. We obtain the number hired from the high productivity sector using ONS job-to-job flow data (ONS (2017*c*)). To find the number hired from the low productivity sector, we obtained the share of graduates in the low productivity sector as $\frac{n^{l,g}}{n^{l,g}+n^{l,ng}} = 0.211$ and assumed that the share of graduates in hires into the low productivity sector was equal to this, so $\frac{h^{l,g,l}}{h^{l,g,l}+h^{l,ng,l}} = 0.211$. We combined this with data on job moves within the low productivity sector to obtain hires of graduates in the low productivity sector from elsewhere in that sector. We obtained estimates of hires of graduates into the low productivity sector from unemployment by combining our estimate of hires into the low productivity sector from unemployment with the assumption that the share on graduates in these hires matched their share in low productivity employment. Using all these data, we find that 27% of hires of graduates by low productivity firms came from unemployment, 43% were from workers employed at high productivity firms and 31% were hired from other low productivity firms. Using a similar approach to estimate hires of non-graduates into the low productivity sector, we find the number of non-graduates hired into the low productivity sector is $h^{l,ng} = \rho^l n^{l,ng} = 0.016$. Of these, 46% of hires of non-graduates by low productivity firms came from unemployment and 54% were hired from other low productivity firms. This evidence shows that only a minority of new hires come from the unemployed, highlighting the importance of modelling job-to-job flows in the UK labour market.

[19] The ONS classifies groups 4-6 as medium skill and groups 7-9 as low skill.

[20] This measure should be treated with caution as it is for London only.

This gives a total of 20 calibration targets, outlined in Table 3.1).

Table 3.1: Calibration Targets

Steady-State Value	Interpretation	Target	Source	This Model
u^g	Graduate Unemployment Rate	0.013	ONS data	0.018
u^{ng}	Non-Graduate Unemployment Rate	0.030	ONS data	0.030
$n^{h,g}$	Emp of Graduates in High Productivity Firms	0.26	ONS data	0.26
$n^{l,g}$	Emp of Graduates in Low Productivity Firms	0.15	ONS data	0.15
$n^{l,ng}$	Emp of non-Graduates in Low Productivity Firms	0.55	ONS data	0.56
$\frac{w^h}{w^l}$	Relative Wage	1.90	ONS data	1.98
ρ^h	Match Continuation in High Productivity Firms	0.98	LFS data	0.99
ρ^l	Match Continuation in Low Productivity Firms	0.97	LFS data	0.98
$h^{h,g}$	Hires of Graduates Into High Productivity Firms	0.005	authors calculation	0.003
$h^{l,g}$	Hires of Graduates Into Low Productivity Firms	0.004	authors calculation	0.003
$h^{l,ng}$	Hires of Non-Graduates Into Low Productivity Firms	0.016	authors calculation	0.015
$\frac{h^{h,g,u}}{h^{h,g}}$	Share of Hires of Graduates by High from U	28%	authors calculation	41%
$\frac{h^{h,g,h}}{h^{h,g}}$	Share of Hires of Graduates by High from High	55%	authors calculation	33%
$\frac{h^{h,g,l}}{h^{h,g}}$	Share of Hires of Graduates by High from Low	17%	authors calculation	26%
$\frac{h^{l,g,u}}{h^{l,g}}$	Share of Hires of Graduates by Low from U	27%	authors calculation	34%
$\frac{h^{l,g,h}}{h^{l,g}}$	Share of Hires of Graduates by Low from High	43%	authors calculation	46%
$\frac{h^{l,g,l}}{h^{l,g}}$	Share of Hires of Graduates by Low from Low	31%	authors calculation	20%
$\frac{h^{l,ng,u}}{h^{l,ng}}$	Share of Hires of Non-Graduates by Low from U	46%	authors calculation	48%
$\frac{h^{l,ng,l}}{h^{l,ng}}$	Share of Hires of Non-Graduates by Low from Low	54%	authors calculation	52%
Y	Aggregate Output	1	normalisation	0.98

Our model comprises 35 parameters. As discussed above, we calibrate $L^g = 0.42$. We use the calibrations and estimates in Faccini et al. (2013) for the UK wherever a parameter of our model corresponds to a similar parameter in that study. Specifically, we follow Faccini et al. (2013) in setting the discount factor as $r = 0.101$, the opportunity cost of employment as $b = 0.58$, [21] the coefficient of risk aversion in utility as $\eta = 0.73$ and the responses of monetary policy to inflation and the output gap as $\phi_\pi = 1.48$ and $\phi_y = 0.31$ respectively. We also assume the elasticities of matching with respect to unemployment for both high and low productivity firms are the same and set them to the elasticity in the aggregate matching function in Faccini et al. (2013), so $\alpha^h = \alpha^h = 0.3$. We assume $\nu^l = 11$. We also calibrate the bargaining power of workers in wage setting in the high productivity firms using the corresponding bargaining power in the aggregate wage bargain in Faccini et al. (2013), so $\zeta^h = 0.87$. For the parameters of the wage- and price-setting relationships, we follow a model developed by the Office of Budget Responsibility (Murray (2012)) and set $\kappa^h = \kappa^l = 0.1$ and $\omega^h = \omega^l = 0.85$. In the absence of previous calibrations for the UK, we set $\varphi^h = \varphi^l = 0.95$.

We calibrate the remaining 19 parameters to match our 20 calibration targets as closely as possible. We set the weight on high productivity retail goods in household utility as $\nu = 2$. We set the exogenous job destruction rates in high and low productivity firms as $\tau^h = 0.001$ and $\tau^l = 0.0125$, respectively. This

[21] The calibration of the model implies steady state values for the high and low productivity wage to be 1.42 and 0.72 respectively, and an average wage of 0.88. So we assume that the opportunity cost of employment is sufficiently low that workers would always choose to be employed.

implies that job matches in high productivity firms are much more likely to be terminated as the result of workers moving to other jobs than by workers moving to unemployment. We set the bargaining power of workers in wage setting in low productivity firms as $\zeta^l = 0.4$, so workers at low productivity firms have less than half the bargaining power of workers at high productivity firms. We set $m^h = 2.2$ and $m^l = 0.98$. The costs of posting vacancies are calibrated as $\gamma^h = 0.4$ and $\gamma^l = 0.24$. The productivities of workers in high and low productivity firms are set as $A^h = 1.5$ and $A^l = 0.80$ respectively, so workers at high productivity firms are almost twice as productive as workers at low productivity firms. We assume $\nu^h = 20$. Finally, we calibrate the various search intensities as $\zeta^{h,g,u} = 0.26$, $\zeta^{l,g,u} = 0.14$, $\zeta^{l,ng,u} = 0.38$, $\zeta^{h,g,h} = 0.009$, $\zeta^{h,g,l} = 0.007$, $\zeta^{l,g,h} = 0.006$, $\zeta^{l,g,l} = 0.004$ and $\zeta^{l,ng,l} = 0.013$. These calibrations are summarised in Table 3.2). As the final column of Table 3.1) shows, our parameter calibration enables us to match our calibration targets closely, although the match is less close for the complex pattern of transitions of workers between unemployment and between different jobs.

Our calibration implies that graduates find it more difficult to find employment than non-graduates, as $f^{h,g} = 0.13$ and $f^{l,g} = 0.14$ in steady-state, compared with $f^{l,ng} = 0.41$. High productivity firms fill their vacancies at a faster rate, as $q^h = 2.01$, compared to $q^l = 0.89$. Although it is more costly for high productivity firms to post vacancies, since $\gamma^h > \gamma^l$, the marginal cost of hiring workers is lower for high productivity firms, since $\frac{\lambda^h}{A^h} = 0.003$, compared to $\frac{\lambda^l}{A^l} = 0.012$, reflecting the faster rate at which high productivity firms fill their vacancies and the higher rate of job destruction at low productivity firms.

Table 3.2: Calibrated Parameters

Parameter	Interpretation	Source/Target	Value
L^g	% Graduates in Labour Force	ONS data	0.420
r	Discount Rate	Faccini et al (2013)	0.0101
ϕ_π	Mon Pol Response to Inflation	Faccini et al (2013)	1.48
ϕ_y	Mon Pol Response to Output	Faccini et al (2013)	0.31
b	Opp Cost of Employment	Faccini et al (2013)	0.58
η	Risk Aversion	Faccini et al (2013)	0.73
α^h	Matching Elasticity for High Prod	Faccini et al (2013)	0.3
α^l	Matching Elasticity for Low Prod	Faccini et al (2013)	0.3
ν^l	Elasticity of Demand for Low Prod	Faccini et al (2013)	11
ζ^h	Bargaining Power for High Prod	Faccini et al (2013)	0.87
ν	% Weight on High Prod Goods in Utility	Authors' Calibration	2
τ^h	Exog Job Destuction in High Productivity Firms	Authors' Calibration	0.0011
τ^l	Exog Job Destuction in Low Productivity Firms	Authors' Calibration	0.0125
m^h	Matching Efficiency for High Productivity Firms	Authors' Calibration	2.15
m^l	Matching Efficiency for Low Productivity Firms	Authors' Calibration	0.8
ζ^l	Bargaining Power for Low Productivity Firms	Authors' Calibration	0.4
ν^h	Elasticity of Demand for High Prod	Authors' Calibration	20
γ^h	Vacancy Cost for High Productivity Firms	Authors' Calibration	0.4
γ^l	Vacancy Cost for Low Productivity Firms	Authors' Calibration	0.24
A^h	Productivity for High Productivity Firms	Authors' Calibration	1.5
A^l	Productivity for Low Productivity Firms	Authors' Calibration	0.80
$\zeta^{h,g,u}$	Search by Unemp Grads for High Prod Jobs	Authors' Calibration	0.1
$\zeta^{l,g,u}$	Search by Unemp Grads for Low Prod Jobs	Authors' Calibration	0.13
$\zeta^{l,ng,u}$	Search by Unemp Non-Grads for Low Prod Jobs	Authors' Calibration	0.355

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Parameter	Interpretation	Source/Target	Value
$\zeta^{h,g,h}$	Search by High Prod Grads for Other High Prod Jobs	Authors' Calibration	0.005
$\zeta^{h,g,l}$	Search by Low Prod Grads for High Prod Jobs	Authors' Calibration	0.0025
$\zeta^{l,g,h}$	Search by High Prod Grads for Low Prod Jobs	Authors' Calibration	0.007
$\zeta^{l,g,l}$	Search by Low Prod Grads for Other Low Prod Jobs	Authors' Calibration	0.0034
$\zeta^{l,ng,l}$	Search by Low Prod Non-Grads for Other Low Prod Jobs	Authors' Calibration	0.015

3.4 Modelling the Pandemic

3.4.1 Modelling the Pandemic Using Shocks

We model the COVID-19 pandemic and the policy measures taken to mitigate this as a series of simultaneous shocks. To model the impact of these, we write the linearised representation of our model as

$$A_0 E_0 X_{k+1} = A_1 X_k + A_2 X_{k-1} + B\epsilon_k^{pan} \tag{3.52}$$

for $k = 1, 2, 3...$, where k is the number or quarters since the pandemic began, X_k is an $(n \times 1)$ vector containing the n endogenous variables of the model; ϵ_k^{pan} is a $(s \times 1)$ vector containing the s shocks that we use to represent the pandemic and policy measures; A_0, A_1 and A_2 are $(n \times n)$ matrices containing the structural parameters of the model, calibrated as decribed in the previous section; and B is an $(n \times s)$ matrix that captures the impact of the shocks on the endogenous variables. To simulate the pandemic, we first specify the shocks in ϵ^{pan}, as described below. We assume the pandemic began in 2020Q2, when $k = 1$; we assume the UK economy was in steady-state (relative to the major disruption that followed) in 2020Q1. We use a deterministic simulation of the model, showing the response of the endogenous variables to the shocks in ϵ^{pan}. We model the shocks as autoregressive processes, so

$$\varepsilon_{t+k}^{z} = \rho^{z} \varepsilon_{t+k-1}^{z} \tag{3.53}$$

where z indexes the shock; so the behaviour of the shock over time is characterised by the incidence in 2020Q2 and the persistence parameter. We begin by specifying a baseline simulation to show the likely impact over 2020-2023, based on information available in June 2020. We then consider alternative scenarios.

Considering how to model the shocks, we first note that the pandemic has reduced the number of workers. Although fatalities had a larger impact on non-graduates, with the mortality for the top three occupational groups substantially below that for other groups, the distribution of self isolation has been more even (ONS (2020*a*)). The pandemic has also reduced aggregate demand, with sharp reductions in consumer spending and a a large reduction in the demand for consumer credit. There has been a marked reduction in consumer confidence. The impact on this has fallen more heavily on areas with a higher proportion of non-graduates, especially leisure, hospitality and entertainment. The pandemic has also led to a surge in job destruction, with almost two million additional claims for Universal Credit between mid-March and the first week of April (DWP (2020)); this was concentrated in non-graduate occupations. In addition, the pandemic has led to a rapid increase in the numbers working at home. Home working is heavily concentrated among graduates (Costa Dias et al. (2020)), with 47% of graduates working at home in late April 2020, compared to around 15% of those with no qualifications (Gustafsson and McCurdy (2020)); related to this, over 50% of workers in managerial and professional occupations were working from home, compared to less than 10% in personal services, process and machine operatives and elementary occupations (*ibid*). Reflecting this, we model the pandemic as a combination of shocks: (i) $\varepsilon^g < 0$ and $\varepsilon^{ng} < 0$, with $\varepsilon^{ng} < \varepsilon^g$; (ii) $\varepsilon^d < 0$; (iii) $\varepsilon^{\Gamma^h} > 0$; (iv) $\varepsilon^{\tau^h} > 0$ and $\varepsilon^{\tau^l} > 0$, with $\varepsilon^{\tau^l} > \varepsilon^{\tau^h}$; and (v) $\varepsilon^{s^h} < 0$ and $\varepsilon^{s^l} < 0$, with $\varepsilon^{s^l} < \varepsilon^{s^h}$. These assumptions are sumarised in the first row of Table 3.3).

The public health response to the pandemic was a "lockdown", leading to the temporary closure of many workplaces and all shops, public spaces and schools, to restrict movements outside the home. We model this as a reduction in aggregate demand, with a larger impact on low productivity firms, reflecting the widespread closure of much of the entertainment and hospitality sectors;[22] also an increase in the rate of job destruction, with again a disproportionate effect on lower productivity firms; and a reduction in the productivity of workers, with a larger impact on the lower productivity sector, due to lower rates of home working. So we assume (i) $\varepsilon^d < 0$; (ii) $\varepsilon^{\Gamma^h} > 0$; (iii) $\varepsilon^{\tau^h} > 0$ and $\varepsilon^{\tau^l} > 0$, with $\varepsilon^{\tau^l} > \varepsilon^{\tau^h}$; and (iv) $\varepsilon^{s^h} < 0$ and $\varepsilon^{s^l} < 0$, with $\varepsilon^{s^l} < \varepsilon^{s^h}$. These assumptions are summarised in the second row of Table 3.3).

The adverse effects of these measures were to some extent offset by the Job Retention Scheme. Through this, the UK Treasury covered 80% of the cost of furloughed workers, up to a limit of £30,000 (slightly above 2019 UK annual median earnings of £29,400). By early May 2020, two thirds of UK firms had applied to the scheme and close to 7.5 million workers were on furlough. Take up was heavily skewed towards workers in lower productivity occupations (Leslie (2020)). The large number of workers on furlough preserved job matches and so reduced the rate of job destruction. By supporting the incomes of workers who would otherwise become unemployed, the Scheme also boosted aggregate demand. But the withdrawal of large numbers of employed workers from work led to a large decline in productivity. So we model a "Job Retention Scheme" as (i) $\varepsilon^d > 0$; (ii) $\varepsilon^{\tau^h} < 0$ and $\varepsilon^{\tau^l} < 0$, with $\varepsilon^{\tau^l} > \varepsilon^{\tau^h}$; (iii) $\varepsilon^{s^h} < 0$ and $\varepsilon^{s^h} < 0$, with $\varepsilon^{s^h} < \varepsilon^{s^h}$; and (iv) $\varepsilon^{w^l} < 0$ and $\varepsilon^{w^h} < 0$, with $\varepsilon^{w^l} < \varepsilon^{w^h}$. These assumptions are summarised in the third row of Table 3.3).

Other governmental responses to the pandemic also had a significant effect on the impact of the pandemic on the economy. In particular, there were large increases in state expenditure on health care, and large increases in Local Authority funding, used to finance a rapid transfer of patients from hospital into care homes, to make room for the rapid expansion in NHS capacity late March 2020, deferrals of VAT and other tax payments; the direct impact of these policy measures on cash borrowing in 2020-21 was forecast by the Office of Budget Responsibility in May 2020 to be £123 billion (OBR (2020)). We model the effect of this as an increase in aggregate demand and an increase in hiring in the low productivity sector reflecting the higher proportion of jobs requiring non-graduates in the health and care sectors, that offset some of the loss of jobs in low productivity firms, so (i) $\varepsilon^d > 0$ and (ii) $\varepsilon^{\tau^l} < 0$. These effects are summarised in the fourth row of Table 3.3).

A strong monetary policy response from the Bank of England provided an additional mitigation to the adverse economic effects of the pandemic. From mid-March 2020, the Bank of England increased the size and scope of it's Quantitative Easing (QE) program, announcing additional purchases of £435bn, alongside other measures to support the financial system and to encourage lending (BoE (2020*b*)). We model the impact of this as a negative shock to the interest rate, so $\varepsilon^i < 0$. These effects are summarised in the fifth row of Table 3.3).

[22]This response is consistent with the prescient simulation in Keogh-Brown et al. (2009).

Table 3.3: The Impact of the Pandemic and Mitigating Policies via Shocks

shocks to	ε^g	ε^{ng}	ε^d	ε^i	ε^{Γ^h}	ε^{τ_h}	ε^{τ_l}	$\varepsilon_t^{s^h}$	$\varepsilon_t^{s^l}$	$\varepsilon_t^{w^h}$	$\varepsilon_t^{w^l}$
Pandemic	↓	↓	↓		↑	↑	↑	↓	↓		
Public Health			↓		↑	↑	↑	↓	↓		
JRS			↑			↓	↓	↓	↓	↓	↓
Fiscal Policy			↑				↓				
Monetary Policy				↓							

3.4.2 Calibration of the Pandemic Shocks

We can classify the shocks in our simulation as being either aggregate supply or aggregate demand shocks, where the former comprise shocks to the workforce, to job destruction, to productivity and to wages. Aggregate demand shocks comprise shocks to monetary policy, to relative demand and to aggregate demand. Considering the aggregate supply shocks first, the main impact of the pandemic on the size of the workforce arose from workers being in self-isolation or sick with COVID-19. The impact of the pandemic on mortality of prime-age individuals in the UK was relatively limited, short in duration and mainly affected workers in health, care and transport occupations (ONS (2020*b*)). At the height of the pandemic in April 2020, 3% of workers were affected in this way, with a fairly even incidence across industries (Costa Dias et al. (2020)). So we calibrate ε_t^g and ε_t^{ng} to generate a 3% reduction in L^g and L^{ng}; we assume that this effect dissipates rapidly, reflecting the strong impact of the lock-down in reducing infection rates, by assumng $\rho^g = \rho^{ng} = 0.05$. In this simulation, we assume there is no "second wave" of infections.[23]

Information on the distribution of job losses by occupation is scarce at the time of writing. But the Resolution Foundation estimated job losses by industry in April 2020 (Tomlinson (2020)), finding that these are concentrated in areas such as Hospitality, Retail and Construction, with high proportions of employment of non-graduates. This is partly offset by an increase in employment in the Health and Care sectors. By contrast, job losses in sectors with higher concentrations of graduates, such as Finance and Insurance and Public Administration, are 5-6 times lower. Based on this evidence, we calibrate $\varepsilon_t^{\tau^l}$ so that the rate of exogenous job destruction in low productivity firms increases to 6.7% at the onset of the crisis. This generates an increase of 1.2 million non-graduates and 200,000 graduates becoming unemployed. We calibrate $\varepsilon_t^{\tau^h}$ so that the rate of exogenous job destruction in high productivity firms increases to 2.9% in 2020Q2; this generates an additional flow of 200,000 newly unemployed graduates. We assume $\rho^{\tau^l} = \rho^{\tau^h} = 0.5$, so the wave of job losses dies away quite rapidly. Together, these shocks lead to an additional 1.6 million job losses at the onset of the pandemic.[24]

To construct the supply shocks for the representative high productivity firms, we define the effective workforce as $n_t^{h,e} = (1 - \pi^{f,h}\omega_t^{f,h} - \pi^{wfh,h}\omega_t^{wfh,h})n_t^h$, where $\omega_t^{f,h}$ and $\omega_t^{wfh,h}$ are the proportions of workers at high priductivity firms who are furloughed and working from home respectively, and $\pi^{wfh,h}$ and $\pi^{wfh,h}$ are the relative productivities of these workers. Since output is $Y_t^h = A_t^h n_t^{h,e}$, output per employed worker is $\frac{A_t^h n_t^{h,e}}{n_t^h} = (1 - \pi^{f,h}\omega_t^{f,h} - \pi^{wfh,h}\omega_t^{wfh,h})A_t^h$. We assume that furloughed workers do not contribute to output, so $\pi^{wfh} = 0$ and that working from home reduces productivity by 10%,

[23] Coibion et al. (2020) have suggested that the pandemic led to the withdrawal of workers from the workforce in the US. The surge in job search activity by new claimants for Universal Credit suggests this effect is small in the UK, Brewer and Handscomb (2020).

[24] This is somewhat above the number of new claims for Universal Credit in this period, but not all workers are eligible for Universal Credit.

so $\pi^{wfh} = 0.9$. We use occupational-level data on the numbers of workers furloughed and working at home in April 2020, constructed by Gustafsson and McCurdy (2020). Using ONS data on employment by occupation, we use these data to construct measures of the share of workers employed in high productivity firms who were furloughed or working from home in April 2020. We adjusted the numbers furloughed to reflect increased take-up of the Job Retention Scheme (JRS) until June 2020, to get estimates for 2020Q2;[25] we find that over 2020Q2, an average of 19.4% of workers at high productivity firms were furloughed, so $\omega_t^{f,h} = 0.194$, and 51.5% of workers at high productivity firms worked from home, so $\omega_t^{wfh,h} = 0.515$. Productivity per employed worker at high productivity firms in 2020Q2 is then (100-19.4-0.1*51.5)=75.5% of the pre-pandemic level. We calibrate the high productivity supply shock so that $e^{\varepsilon_t^{s^h}} = (1 - \pi^{f,h}\omega_t^{f,h} - \pi^{wfh,h}\omega_t^{wfh,h})$ matches this figure. We also find that over 2020Q2, an average of 21% of workers at low productivity firms were furloughed and 17% were working from home. Productivity per employed worker at the representative low productivity firm in 2020Q2 is then (100-21.4-0.1*17)=77.1% of the pre-pandemic level. We calibrate the low productivity supply shock to match this. We assume $\rho^{s^h} = \rho^{s^l} = 0.25$.

To calculate the impact of the Job Retention Scheme on wages, we first consider the representative low productivity firm. We express the wages paid by this firm as $\{\omega_t^{f,l}(1 - \phi_t^{f,l}) + (1 - \omega_t^{f,l})\}w_t^l$, where $\phi_t^{f,l}$ is the share of the wage paid by the state under the JRS. The Job Retention Scheme paid 80% of the wages of furloughed workers, up to a limit of £30,000, close to the median wage; so we assume $\phi_t^{f,l} = 0.8$. This implies that the wage cost to the representative low productivity firm is 21*0.2+79 or 83.2% of the wage. We calibrate the wage shock for low productivity firms to match this. We express the wages paid by the representative high productivity firm as $\{\omega_t^{f,h}(1-\phi_t^{f,h})+(1-\omega_t^{f,h})\}w_t^h$, where $\phi_t^{f,h}$ is the share of the wage paid by the state under the JRS. The calculation here is less straightforward since the wage in these firms will be above the median. Here we assume that the JRS pays 40% of the wage, so $\phi_t^{f,l} = 0.4$. This implies that the wage cost to the representative high productivity firm is 19.4*0.6+80.6 or 92.2% of the wage. We calibrate the wage shock for high productivity firms to match this. Reflecting the short duration of the JRS, we assume $\rho^{w^h} = \rho^{w^l} = 0.15$.

To model the impacts of the pandemic on aggregate demand, we calibrate ε^i so that the (shadow) interest rate decreases by 250 basis points in 2020Q2; we assume $\rho^i = 0.75$, so this effect is relatively persistent. Initial estimates of GDP for April 2020 suggest much sharper falls in output in hospitality and retail industries, with a lower fall in output that makes greater use of graduates. To model this, we calibrate ε^{Γ^h} so that the fall in demand for the output of high productivity firms is 25% smaller than the fall in demand for the output of low productivity firms. Finally, we calibrate the aggregate demand shock ε^d to match the projected reduction in UK GDP in June 2020. Here, there is little consensus. The May 2020 Bank of England *Monetary Policy Report* projects a reduction of 14% in the main illustrative baseline scenario (BoE (2020*a*)). The OECD expects a falls of 11.4% (OECD (2020)), while the IMF projects a fall of 10.2% (IMF (2020)). We calibrate ε^d to generate a fall in UK GDP over 2020 of 11%.

Table 3.4: The Baseline and Alternative Scenario

Impact	(i) Baseline	(ii) Scenario 1
L^g	$\downarrow$ 3%	$\downarrow$ 3%
L^{ng}	$\downarrow$ 3%	$\downarrow$ 3%
τ^h	$\uparrow$ 168%	$\uparrow$ 168%
τ^l	$\uparrow$ 335%	$\uparrow$ 168%

continued ...

[25]The number of workers furloughed using the JRS increased from 3.8 million in April 2020 to 8.9 million in June 2020. For 2020Q2 as a whole, we used the average of these figures. We assumed that the numbers working from home did not change between April-June 2020.

. . . continued

Impact	(i) Baseline	(ii) Scenario 1
A^h	$\downarrow$ 24.5%	$\downarrow$ 24.5%
A^l	$\downarrow$ 22.9%	$\downarrow$ 24.5%
w^h	$\downarrow$ 7.8%	$\downarrow$ 7.8%
w^l	$\downarrow$ 17.0%	$\downarrow$ 7.8%
i	$\downarrow$ 250bp	$\downarrow$ 250bp
$\frac{Y^h}{Y^l}$	$\uparrow$ 25.0%	
Y^d	$\downarrow$ 11.0%	$\downarrow$ 11.0%

3.4.3 Baseline Scenario

The calibration of shocks in our baseline simulation, as outlined above, are contained in column (i) of Table 3.4). The results of our baseline simulation is shown in Figure 3.2). We begin by considering the aggregate impacts. Our model projects a relatively quick recovery in output, which returns to pre-pandemic levels by mid-2021. The recovery in other variables is slower. Unemployment increases to 2.97 million workers, an unemployment rate of 8.7%, by 2020Q3; this is close to the forecast of 9% in the Bank of England's *Monetary Policy Report* of May 2020 (BoE (2020*a*)). The recovery in the unemployment rate is slow; it does not return to pre-pandemic levels until 2022. Employment falls by 6.6% by the end of 2020 and remains below pre-pandemic values until 2021. The real wage falls by 0.9%; this recovers quickly and exceeds the pre-pandemic level by early 2022.[26] Our scenario projects deflation of -2% in 2020, followed by several years of above-target inflation, rising to 4% during the recovery from the pandemic. However, this should be treated with some caution.[27]

Turning to the main focus of our paper, our simulations reveal that the pandemic has very different impacts on different types of worker. Job losses affect non-graduates much more severely than graduates. Nearly 1.2 million non-graduates lose their jobs by the end of 2020, compared to 0.4 million job losses among graduates. The unemployment rate of non-graduates rises to 10.1% compared to 6.8% for graduates; by the end of 2020Q3, 2.0 million non-graduates are unemployed, compared to just below 1 million graduates. The real wages of non-graduates fall by 2.0%, whereas wages of graduates employed in high productivity firms fall by 1.9%. The employment of different types of worker differs markedly across the pandemic. Employment of non-graduates in low productivity firms falls by 8.1% by the end of 2020 and reaches pre-pandemic values by mid-2021. The structure of graduate employment changes markedly and the adjustment back to previous values lasts beyond 2024. Employment of graduates in high productivity firms declines slightly but then increases, driven by the increased demand for the output of high productivity firms. By contrast, employment of graduates in non-graduate roles falls 9.6%. Employment of graduates in these different types of firm only returns slowly to pre-pandemic levels, with the adjustment lasting beyond 2023. Interestingly, our model predicts a rise in productivity as the proportion of graduates employed in lower productivity firms declines. The different experience of different workers gives rise to the composition effects similar to those raised in Solon et al. (1994), and more recently, during the pandemic, Rouse and Gimbel (2021). The the result shows that the average wage falls by less than the wages paid by high productivity and low productivity firms, due to the rise

[26] If we use $\varphi^{w,h} = \varphi^{w,l} = 0.85$, the real wage falls by 5.4%.

[27] For two reasons; first, inflation is especially difficult to forecast during the pandemic as adverse demand and supply shocks move it in different directions, in contrast to the effect of these shocks on output, employment and unemployment; and second, our simple model does not allow for variations in the mark-up. There is evidence that increased mark-ups increased inflation from 2020Q2, as major retailers ceased competitive price reductions (Jaravel and O'Connell (2020)).

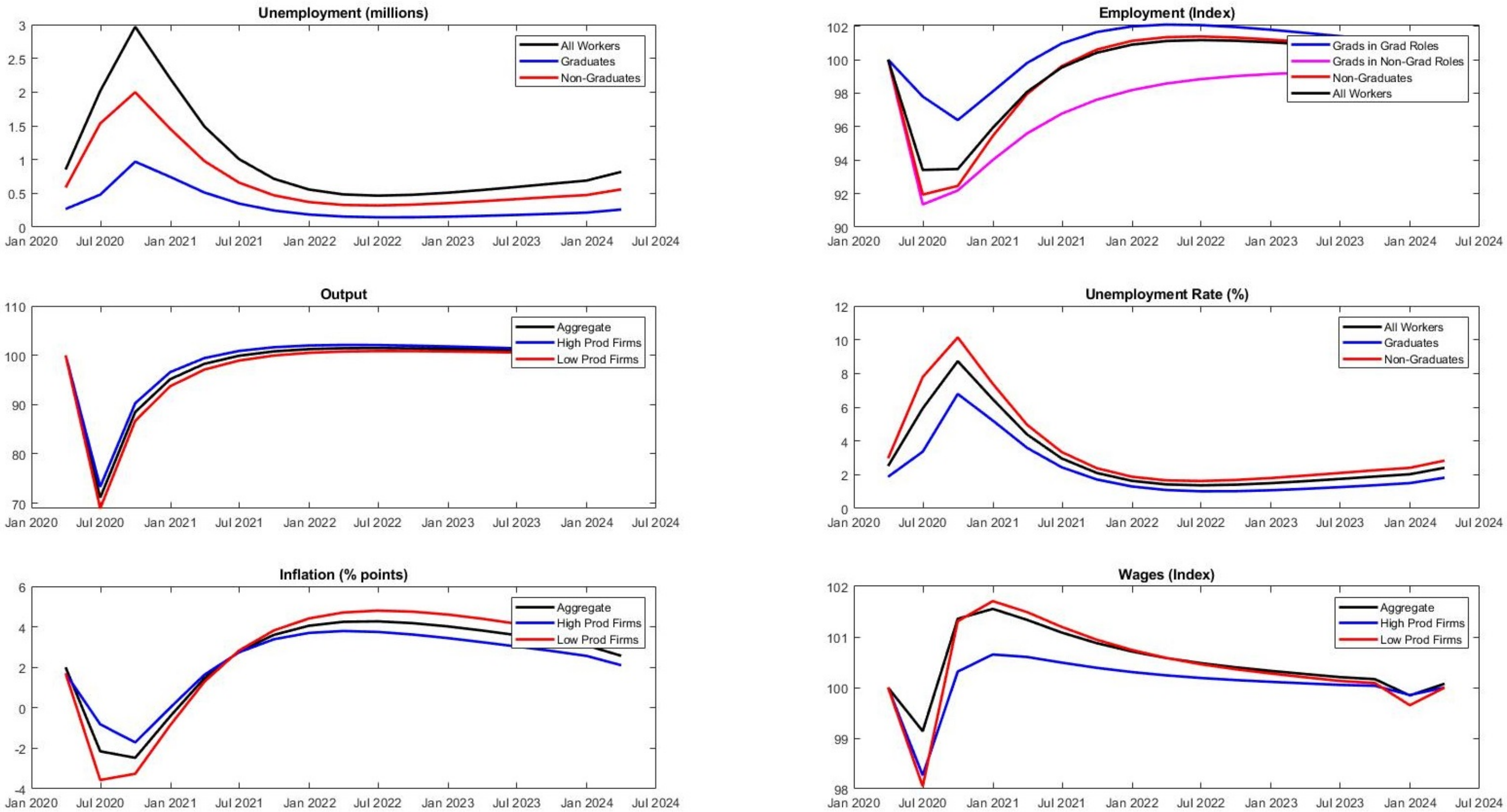

Figure 3.2: The Baseline Model

Notes: The top left panel of this figure plots the numbers of unemployed workers (solid black line), the number of unemployed non-graduates (solid red line) and the number of unemployed graduates in the baseline scenario (solid blue line). The top right panel plots indices for total employment (solid black line), graduates in high productivity firms (solid blue line), graduates in low productivity firms (solid pink line) and non-graduates in low productivity firms in the baseline (solid red line). The middle left panel plots indices for total output (solid black line), output of high productivity firms (solid blue line and output of low productivity firms (solid red line). The middle left panel plots the unemployment rate of all workers (solid black line), graduates (solid blue line) and non-graduates (solid red line). The bottom left panel plots the aggregate inflation rate (solid black line) and the inflation rates of high productivity firms (solid blue line) and low productivity firms (solid red line). The bottom right panel plots indices for the aggregate wage (solid black line) and real wages in high productivity firms (solid blue line) and low productivity firms (solid red line).

in the share of employment at higher wage high productivity firms resulting from the high rate of low productivity job loss. Without this composition effect, the real wage would fall by 1.9%. Workers in low-paying jobs have been harder hit by the pandemic. This implies that a larger proportion of low-paid workers

Similarly, the shift in consumption towards the, output of high productivity firms moderates the fall in inflation; the inflation rate would reach -2.9% without this composition effect.

3.4.4 Shocks or Structure?

The labour market experience of non-graduates during the pandemic is clearly worse than that of graduates. This reflects both the structure of the economy, since graduates employed by high productivity firms have higher wages and greater job security than non-graduates, and the nature of the shocks caused by the pandemic, which concentrated job losses in low productivity firms and led to larger falls in demand for these firms. To study the relative impact of these, we construct a counterfactual scenario in which the adverse shocks affecting high and low productivity firms are equal. To do this, we amend the shocks as in column (ii) of Table 3.4), so the impact of the pandemic on job destruction, productivity and wages is the same for high and low productivity firms, and there is no shift in demand towards the output of high productivity firms.

The results, shown in Figure 3.3), reveal how the shocks associated with the pandemic have increased the disadvantage of non-graduates in the UK labour market. Unemployment of non-graduates continues to exceed unemployment of graduates, but the gap between them narrows. Unemployment of non-graduates decreases from 2.18 million to 1.72 million. The percentage fall in employment of non-graduates is now similar to that of graduates employed in high productivity firms; in contrast to the baseline scenario. The proportional fall in wages in high and low productivity firms is now also more similar, with non-graduate wages falling by 2.8%, compared to 3.4% in the baseline. As a consequence, the rate of deflation is reduced.

3.5 Conclusions

There has been no event similar to the COVID-19 pandemic in recent history. At the time of writing this chapter, the full impact of the pandemic is still unknown, but there is little doubt that it will shape the economy in the years to come. From the onset of the pandemic and Lockdown in the UK, some patterns in the labour market and economy were clear: there was a reduction in the number of workers in the labour market due to the disease, a decrease in demand and productivity, job loss, and there were differing impacts for different sectors and types of worker.

We examined the impact of the pandemic on graduates and non-graduates in the UK. Sectors with higher proportions of non-graduates were harder hit by the pandemic than sectors with more graduate roles, but even in the absence of this difference, our model showed that non-graduates were still slightly worse-off than graduates because their productivity and employment opportunities are less than those of graduates.

Our model recognises the difference in the labour market experience for graduates and non-graduates in the UK is a useful base for evaluating and formulating targeted policy interventions. As the impacts of the pandemic unravel, it wiill become possible to simulate more precise magnitudes for the shocks in the model. The model can also be extended to include economic inactivity and movements of workers in and out of the labour force, or adjusted to model the experiences of employees in permanent employment compared to the self-employed and gig workers, and how the pandemic and policy interventions have impacted these types of worker.

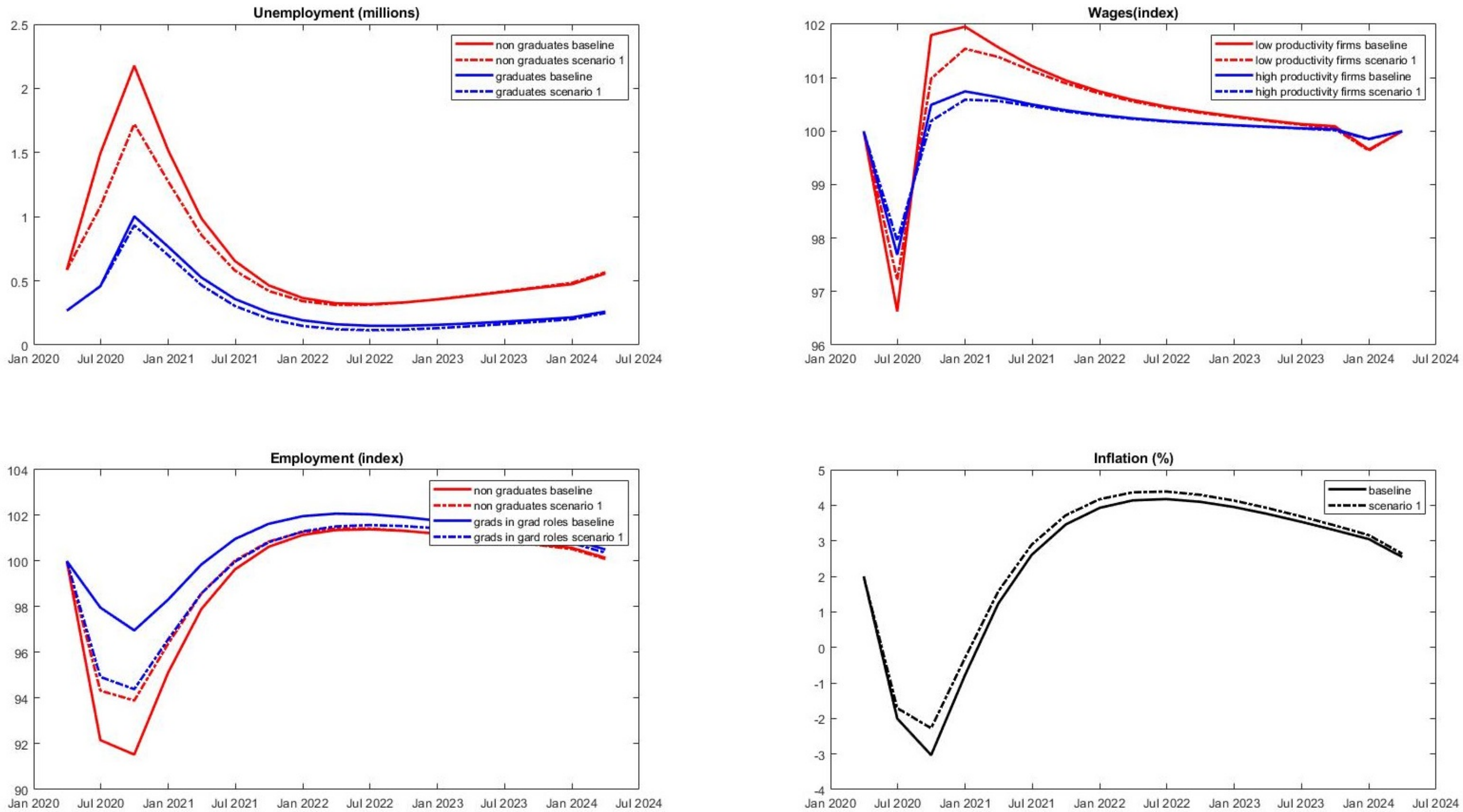

Figure 3.3: Scenario 1: The Same Shocks

Notes: The top left panel of this figure plots the number of unemployed non-graduates in the baseline scenario (solid red line) and the scenario (dotted red line) and the number of unemployed graduates in the baseline scenario (solid blue line) and the scenario (dotted blue line). The top right panel plots wages of high productivity firms in the baseline (solid blue line) and the scenario (dotted blue line) and wages of low productivity firms in the baseline (solid red line) and the scenario (dotted red line). The bottom left panel plots employment of graduates in high productivity firms in the baseline (solid blue line) and the scenario (dotted blue line) and employment of non-graduates in low productivity firms in the baseline (solid red line) and the scenario (dotted red line). The bottom right panel plots the inflation rate in the baseline (solid black line) and the scenario (dotted black line).

3.6 Addendum

Since the start of the pandemic in the UK, there have been three lockdowns of varying severity, and according to the Office for National Statistics Business Insights and Conditions Survey for May 2021, 3.9% of businesses across all industries have permanently stopped trading. ONS estimates for May 2021 also show that about 75.9% of adults in England have tested positive for COVID-19 antibodies, 76.6% in Wales, 75.0% in Northern Ireland, and 68.6% in Scotland. This chapter was completed in mid-2020 using early projections of the scale of the impact of the pandemic to analyse the possible effects on the wage, output, inflation, graduate and non-graduate employment and unemployment. In this section, I look back on the results of the model presented in this chapter and comment on them in light of more recent macroeconomic data.

The actual data are presented in Fig. 3.4). Closely following the forecast of 9% unemployment projected by the Bank of England's *Monetary Policy Report* of May 2020, our model projected that unemployment would reach 8.7% by 2020Q3, output will fall by 14%, while employment would fall by 6.6% by the end of 2020. The actual impact of the pandemic on unemployment and employment seen in the data is significantly less than the early BoE projection and the projection of our model. The data show that unemployment only rose to 4.8% in 2020Q3, being 1% point higher than the unemployment rate in 2019Q3, and peaked at 5.1% in 2020Q4. The data also show that employment fell by about 1.3% points in 2020Q4. However, LFS data should be taken with caution because of issues with reporting employment and unemployment, and changes in the composition of the survey participants and jobs during the pandemic. For example, the May 2021 BoE Monetary Policy Report highlights discrepancies between the number of employees reported in the Labour Force Survey, and employees reported in the Workforce Job Survey and PAYE data. The PAYE and Workforce Job Survey show larger declines in the number of employees, whereas employee numbers reported in the LFS is stable. One explanation for this proposed in the report is workers reclassifying their employment status from self-employed to employee. In addition, the ONS reports that because face-to-face interviews were largely replaced by phone interviews with lower response rates, the LFS data during the pandemic may be less representative of the pre-pandemic sample.[28] Another explanation by the ONS worth noting is the difficulty in defining employment status during the pandemic; there are workers who have done no work, have not been furloughed, and have received no wages during the pandemic, who report as being employed because they expect to return to their former job after the pandemic.[29]

The overprediction of the impact of the pandemic on unemployment in our model has important implications for the projections for inflation, output and wages. Our model predicts 2% deflation by the end of 2020, but actual inflation was at the lowest in August 2020 at 0.2%. ONS data show that output fell by about 15.8% points between 2020Q1 and 2020Q2, but had recovered by about 12% points by 2020Q3, whereas, our model predicted a 30% fall in aggregate output.

On a final note, it is worth pointing out the transition dynamics between employment, unemployment and inactivity during the pandemic. The model presented in this chapter does not include the economically inactive. However, unemployment-inactivity transitions have been widely analysed in the literature, and there is evidence that during recessions, there is an increase in the transition of workers from inactivity into unemployment and a fall in the number leaving unemployment to inactivity (Elsby et al. (2015)). These unemployment-inactivity transitions can explain a significant proportion of the fluctuations in unemployment across the business cycle (Gomes (2012), Razzu and Singleton (2016), Singleton (2018)).

Fig. 3.5) shows the flows of workers between unemployment and inactivity during the pandemic using

[28]https://blog.ons.gov.uk/2020/10/12/measuring-the-labour-market-during-the-pandemic/

[29]https://blog.ons.gov.uk/2020/07/16/a-covid-19-conundrum-why-are-nearly-half-a-million-employees-not-being-paid/

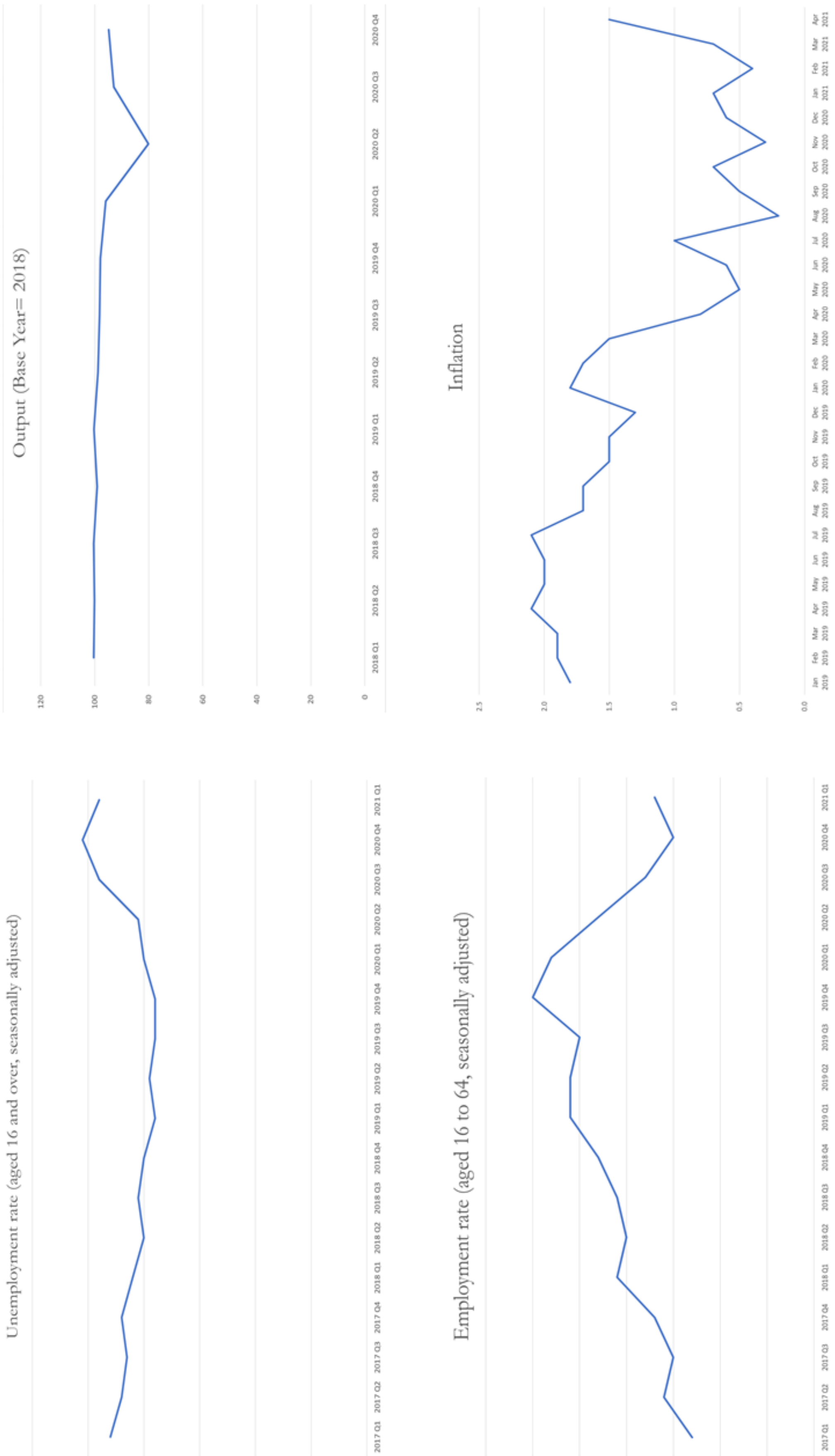

Figure 3.4: Actual Data for Unemployment, Employment Output and Inflation
Note: Plots are derived from data from the Office for National Statistics.

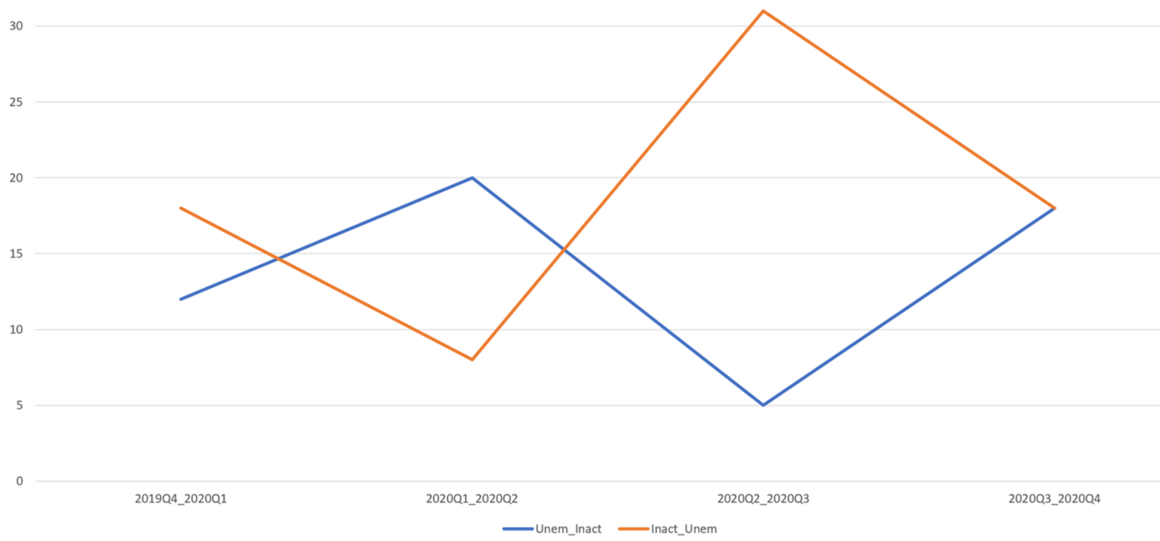

Figure 3.5: Transitions between Unemployment and Inactivity during the Pandemic
Note: Plots are derived from data from the Office for National Statistics.

LFS data. The figure shows an increase in the number of workers transitioning from unemployment to inactivity, and a sharp decrease in the transition from inactivity to unemployment between 2020Q1 and 2020Q2, and between 2020Q3 and 2020Q4. The figure also shows that the reverse occurs between 2020Q2 and 2020Q3. These changes might be significant because they might reflect the labour market response to the first and second lockdown, and the early announcements of changes to the Job Retention Scheme which may not have been captured in our model.

A later version of the model presented in this chapter attempts to resolve the points raised in this section. In the later version, we use the latest LFS data, noting the possible shortcomings of the LFS during the pandemic. We also combine the unemployed and economically inactive to present a broader view of the labour market and the dynamics during the pandemic for graduates and non-graduates in different statuses and types of employment in the UK.

4 The Impact of the Rising Gig Economy on UK Wages and Output

Appendix 6B: Statement of Authorship

This declaration concerns the article entitled:	
The Impact of the Rising Gig Economy on UK Wages and Output	
Publication status (tick one)	
Draft manuscript X **Submitted** ☐ **In review** ☐ **Accepted** ☐ **Published** ☐	
Publication details (reference)	
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Candidate's contribution to the paper (provide details, and also indicate as a percentage)	The candidate contributed to / considerably contributed to / predominantly executed the… Formulation of ideas: 100% Design of methodology: The methodology used in this chapter is adapted from the research in the previous chapter which is joint work with Prof. Chris Martin. My contribution to the methodology is 75%. Experimental work: 100% Presentation of data in journal format: 100%
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.
Signed	**Date** 2/2/21

Last update: Feb 2019

4.1 Introduction

The nature of work in the UK is changing. Over the past three decades, the term "employee" has become less synonymous with being a worker as a growing proportion of the workforce has turned to self-employment, and firms substitute long-term career employees with contingent workers and contractors. In the UK, self-employment increased from 8% of the workforce in 1980 to about 16% in 2016. Also, in 1990, about 30% of self-employed workers employed other workers, but as at 2016, more self-employed workers have chosen work alone and only 16% employ other workers (ONS (2016*b*)). Between 2010 and 2016, the number of part-time workers increased from about 6.6 million to about 7 million workers while zero-hour contracts increased from about 170,000 to over a million workers (Blanchflower et al. (2017), Haldane (2017), ONS (2019)). Compared to the EU, the UK has the highest proportion of the workforce engaged in self-employment and part-time work (Taylor et al. (2017)). These workers often engage in non-employee work, just-in-time, on-demand, contingent or alternative work arrangements which are collectively referred to as gig work. Gig jobs are characterised by high turnover and flexibility, irregular working hours, and are usually created on demand with no certainty of future engagement with the firm.

It is argued that the gig economy increases the efficiency of labour allocation, promotes creativity and entrepreneurship, flexibility and time to meet non-work commitments, offers work experience across different sectors and locations, and provides employment opportunities for the long-term unemployed and the unemployable (Hurst and Pugsley (2011), Katz and Greenwald (2012), Taylor et al. (2017)).[1] However, it has also been argued that the transient employer-employee relationships and the basic, highly fragmented tasks which characterise gig work can lead to poor wages, job insecurity and the potential decline of the structure of modern-day firms and industries (Haldane (2017), Katz and Greenwald (2012)). Gig jobs often attract lower wages than the same type of job in the traditional sector (Freidman (2014), Katz and Krueger (2019)); there is evidence that firms in the UK can save up to 70% on their wage bill from hiring online gig workers instead of traditional workers, and online gig workers in the UK and EU are worse off than the average traditional worker in the same country (Gomez-Herrera et al. (2017)). However, it is worth mentioning that due to exchange rate differences between high- and low-income countries, online gig workers in low-income countries might earn higher wages than their peers in traditional jobs when they are employed by firms in high-income countries (*ibid.*).[2] UK zero-hour contract workers earn 35% less per hour than the median hourly wage for all other types of worker, and 10% less per hour after controlling for differences in characteristics across jobs (Adams and Prassl (2018)). Also, the modal earning of self-employed workers is about £160 less than the modal employee wage (ONS (2018*c*)). Furthermore, male part-time workers in the UK earn less than their counterparts in full-time jobs even after controlling for differences in skill and job characteristics (O'Dorchai et al. (2007)), the wage for full-time work in the UK is more likely to increase while the wage for part-time work is more likely to decrease. There is also evidence of wage scarring, that is, the adverse impact of part-time work on earnings remains after workers transition into full-time jobs (Fouarge and Muffels (2009)).

On a different note, from 2011 to 2020Q1, the UK unemployment rate fell, and at 3.8% in 2020Q1, unemployment was at its lowest in over 40 years.[3] Since 2011, job vacancies reached record numbers,[4]

[1] Also, the irregular nature of some gig jobs implies that gig employment may be underreported. The US household employment survey classifies individuals as employed if they have received a wage or profit for work done in the previous week. Primary survey data by Bracha and Burke (2016) indicates that the 2015 US labour force participation rate would be about 2% points higher if all gig workers were counted.

[2] Differences in exchange rates may also explain the evidence that the worldwide average online gig wage is higher than the worldwide average traditional wage (Gomez-Herrera et al. (2017)).

[3] www.ons.gov.uk/employmentandlabourmarket/peoplenotinwork/unemployment/timeseries/mgsx/lms

[4] www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/uklabourmarket/june2020#vacancies

yet, the real wage and output growth were relatively flat.[5] Other OECD countries show a similar trend (Bell and Blanchflower (2018*a*)).

In this chapter, I describe the UK gig economy and the factors that may be responsible for the rising trend of gig work in the UK. Using the characteristics of the gig economy that I describe below, I construct a two-sector model with a labour market characterised by search frictions to show why the wage for gig work differs from the wage for a similar job in the traditional sector. I then simulate the impact of demand and supply shocks to show how the gig economy changes the macroeconomic response to shocks, and how this might contribute to the slow wage and output growth in the UK.

There are three main factors in the literature which explain the expansion of the UK gig economy in the past 30 years. Firstly, declining trade union membership, loss of bargaining power and rising unemployment encourage the transfer of training costs, business and economic risk to workers, increases job loss and lowers wages (Deakin and Reed (2000), Haldane (2017), Freidman (2014), Katz and Greenwald (2012), Solow (2015)). Few unions and collective bodies exist for gig workers[6] and gig workers have strong conflicting opinions on collective action and regulation. Survey evidence indicates that gig workers face adverse work conditions and are often exploited by firms, but many feel that unionisation or regulation would restrict their flexibility and competitiveness (CIPD (2017), Katz and Greenwald (2012)). The CIPD (2017) UK survey found that 57% of gig workers strongly agree that firms exploit the lack of gig economy regulation, 70% feel that they are less able than traditional workers to access financial safety nets, 63% feel that the government should enforce basic rights and benefits for gig workers, but 50% would sacrifice benefits and security for the flexibility they enjoy from the lack of regulation in the gig sector and 17% would not report a complaint or seek compensation.[7] On the firms' side, survey evidence shows that UK firms with mid-range levels of unionisation are highly likely to employ contingency workers, but firms with high and low levels of unionisation have markedly low numbers of gig workers (Uzzi and Barsness (1998)). The evidence points to the fact that high rates of union participation prevents firms from hiring gig workers, and low levels of union membership means that permanent workers can be made as flexible as firms require with little hinderance (*ibid.*).[8] The latter suggests more serious implications for the quality and future of traditional work.

Secondly, there is evidence that the uptake of gig work is countercyclical and an indicator of labour market slack (Bell and Blanchflower (2018*a*), Bracha and Burke (2016))[9]. For example, participation in gig work fell as unemployment fell during the first internet boom between 1995 and 2000, and increased when unemployment increased at the end of the internet boom. A similar response was observed during the Financial Crisis.[10] This is because in a downturn, workers who have held traditional jobs take gig employment when unable to find other traditional jobs and are facing financial hardship. These workers return to traditional employment after economic recovery.

The third factor is technological advancement and automation, and there is some discord on their impact on the labour market and macroeconomy. There is substantial evidence that automation and artificial intelligence (AI) substitute for labour and hinder the development and demand for skilled labour (Beaudry et al. (2016), Brynjolfsson and McAfee (2014), Frey and Osbourne (2017)). But there is equally

[5]See www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/averageweeklyearningsingreatbritain/january2020#: :text=In%20real%20terms%2C%20annual%20pay,(unchanged%20from%20last%20month) for wage growth and www.ons.gov.uk/economy/grossdomesticproductgdp/timeseries/ihyp/pn2 for output growth.

[6]eg. the Independent Drivers' Guild for Uber drivers, the Freelancers' Union for freelance workers, Sharing Economy UK (SEUK) and most notably, the Independent Workers of Great Britain (IWGB).

[7]The survey was mainly focused on online gig workers.

[8]This has given rise to terms such as *permatemps* which is used to describe contingency workers on extended or rolling contracts with firms.

[9]These studies focus on gig work participation on the intensive margin.

[10]During the Financial Crisis, the number of part-time workers looking for full-time jobs and small business entrepreneurs increased. See Fairlie (2013), Green and Livanos (2015), ONS (2020*d*), ONS (2018*b*).

strong evidence that automation creates more jobs than it destroys; a UK study by Deloitte showed that for each job lost to technology, over 4 new jobs are created, and the wages of the new jobs are, on average, £10,000 higher.[11] In either case, there is little dispute that Information Technology, apps and devices, automation and AI are *changing* the nature of work and the types of worker required to fill job positions. With Information Technology, AI and automation, workers can find work and perform tasks remotely and often in isolation, firms can coordinate workers remotely with ease, making tasks highly fragmented, specialised and polarised (Beaudry et al. (2016), Brynjolfsson and McAfee (2014), Frey and Osbourne (2017), Goos and Manning (2007), Katz and Krueger (2017)). Survey evidence shows that UK firms that implemented new job-related technologies in the preceding three years were more likely to hire temporary workers to perform tasks which were executed by permanent employees (Uzzi and Barsness (1998));[12] this suggests that technology might induce the creation of more gig jobs and might also encourage more workers to take them.

Before proceeding to describe the characteristics of the UK gig economy, it is pertinent to note that there is no unified definition of gig employment in the literature. Gig employment is often used to describe online or app-based work, but I do not use this definition because of the evidence that the number of workers engaged in offline gig work is about twice the number of online gig workers (Katz and Krueger (2019). Instead, I adopt the definition used by Adams-Prassl et al. (2020), Bracha and Burke (2016), Freidman (2014), Katz and Greenwald (2012) and Katz and Krueger (2019), and distinguish gig work from traditional work by the type of job contract the workers have with the firm. Gig work comprises lone-working self-employment, independent contract and consulting jobs, freelance, on-call, part-time,[13] temporary, agency and zero-hour contract work. I identify gig workers in the data as the lone-working self-employed whose work hours vary and workers in temporary, agency, casual and seasonal work. Traditional jobs have regular working hours, open-ended contracts and long-term career prospects with the firm. I identify workers in this category as the self-employed who employ other workers, the lone-working self-employed whose hours do not vary and workers who are in permanent work.[14]

The gig sector has a range of jobs identical to the traditional sector because workers often take gig jobs similar to the traditional jobs they have held in the past (Freidman (2014)) and because workers often use gig employment as a stepping-stone to the traditional job they aspire to have (Booth et al. (2002)). However, there is evidence that productivity is lower in the gig sector because there is a greater proportion of low-skilled, labour intensive jobs in the gig sector than in the traditional sector. For example, in the UK, there are more temporary workers in wholesale and retail trade, health and social work, education, accommodation and food, arts and entertainment; whereas, temporary workers are fewer in manufacturing, professional, scientific, technical, public administration, finance, information and communication occupations (Forde and Slater (2001), Forde and Slater (2005), ONS (2018*a*)). Furthermore, due to the high turnover rate associated with gig work, workers and firms in the gig economy often do not engage in costly training (Booth et al. (2002), Forde and Slater (2005)).

In this model, traditional wholesale firms offer traditional jobs and use a technology that requires only inflexible labour which traditional workers provide. Similarly, gig wholesale firms offer gig jobs and use only flexible labour which gig workers provide. In spite of the evidence that jobs in the traditional sector often attract higher wages than the same job in the gig sector, traditional jobs cannot be said to be strictly better than gig work, at least, from the perspective of individual workers. The data shows

[11]https://www2.deloitte.com/content/dam/Deloitte/uk/Documents/Growth/deloitte-uk-insights-from-brawns-to-brain.pdf

[12]Also, a US survey found that firms that implemented new job-related technologies lowered the skill requirements of jobs, offered lower wages and fewer prospects of career progression (Roos and Reskin (1992)).

[13]Part-time workers are included in this definition to account for the substantial number of workers who hold part-time jobs for economic reasons and want full-time jobs and/or workers who hold multiple part-time jobs which together do not make up full-time employment (Bell and Blanchflower (2011), Bell and Blanchflower (2018*b*)).

[14]I expatiate on the categories of worker in Section 4.8.

that workers take gig jobs when unable to find traditional employment, to increase income, particularly when facing redundancy or retirement, to meet a demand in the market, for better work conditions and job satisfaction, to manage unpaid care/family responsibilities, illness, disability or full-time education, or simply because gig work is the nature of their career. The data also shows that workers' reasons for gig work change randomly over their lifetime. Therefore, I assume that job search is random and continuous. Following the evidence outlined, I also assume that the traditional sector is characterised by a higher bargaining power and productivity than the gig sector.

I assume that unemployed workers search for gig and traditional jobs, will take the job they find and continue searching for other jobs. Gig jobs are short-lived, so I assume that all gig jobs end after one period.[15] Workers in gig employment search for traditional employment and other gig jobs.[16] This means that at the end of a gig job, a gig worker can be re-hired by the same firm, find another gig job or move to traditional employment; otherwise, the gig worker returns to the search pool as unemployed and is not eligible for employment until the next period. On the other hand, workers in the traditional sector are in a more secure form of employment; the data shows very small traditional-traditional job transition. Therefore, I assume that workers in traditional employment do not search for other traditional jobs, but search for gig work. When traditional job matches end, the workers return to the search pool as unemployed and are not eligible for work until the next period. Some traditional job matches survive but the workers move to gig employment.

Following the evidence above, the model will show how the lower productivity and bargaining power in the gig sector leads to lower wages for gig workers than traditional workers doing the same job. Also, gig jobs are flexible and are created on a task-by-task basis, and workers consider gig work to be a substitute for traditional employment (Bracha and Burke (2016)). As such, economic downturn and recovery are characterised by a flow of unemployed workers into gig employment due to hardship (*ibid.*), and in particular, engaging in low-paid self-employment (Blundell et al. (2013), Fairlie (2013)). More workers joining the gig economy can stabilise employment and facilitate economic recovery. However, this may result in slack in the gig sector which, combined with the relatively low productivity in the sector, can lower the wage and output growth in the gig sector and the whole economy.[17] The model will show that the segmented nature of the UK labour market can imply low job finding rates from unemployment, and low- to low-wage job transitions which can exacerbate slow wage and output growth (Danninger (2016)).[18]

This chapter contributes to the existing literature in two significant ways: Firstly, most of the studies on gig working are in form of surveys and reports,[19] and often focus on online or app-based gig jobs. In this chapter, I attempt to capture the entire gig economy by including both online and offline gig workers. Secondly, academic rersearch on the gig economy and the impact on the macroeconomy are less common, and are often carried out on the US labour market.[20] Here, I use the UK Labour Force Survey data to construct a two-sector model that describes the gig and traditional sectors of the UK. Dual sector models have been used to analyse the formal and informal sectors (eg Castillo and Montoro (2012*a*)) and graduates and non-graduates in different types of jobs in the UK (eg Martin and Okolo (2020)). The model described in this chapter shares features with the model in (Martin and Okolo (2020). I subject

[15] The 2019 Q3 LFS shows that 39.1% of gig jobs do not have fixed duration and an additional 16.7% have a duration less than 6 months.

[16] There is strong evidence that traditional workers take gig jobs with the intention of transitioning to traditional jobs (Booth et al. (2002), de Graaf et al. (2011), Farber (2010), Farber (2011)), Gebel (2010)).

[17] For instance, between 2008 and 2015, there was a 20% drop in the real wage of lone-working self-employed workers, but traditional workers and the self-employed who hire additional workers faced milder real wage decrease (Blanchflower et al, 2017). I discuss this in more detail later in the paper.

[18] See also Gash (2008) for discussions on dual labour markets and workers being 'trapped' in temporary employment.

[19] For example, The Good work: The Taylor Review of Modern Working Practices by Taylor et al. (2017), surveys by the Chartered Institute of Personnel Development (CIPD) and the Department for Business Innovation and Skills (DBIS).

[20] The most prominent are Bracha and Burke (2016; 2021)

the model to productivity shocks in the traditional and gig sectors, aggregate demand and supply shocks and analyse the impact of these shocks on unemployment, employment, wages and output.

4.2 The Model

4.2.1 The Labour Market

There is one type of worker and two sectors: the gig and traditional sectors. Workers search for work in both sectors, will take the job that they get and continue searching for the job they want. So workers can be unemployed u, in traditional employment n^{tr} or in gig employment n^g

$$u_t + n_t^{tr} + n_t^g = 1 \tag{4.1}$$

where the labour force is normalised to 1.

Gig jobs are short-lived so I assume that they have a duration of one period. This means that at the start of each period, workers previously in gig employment face four possibilities: *i*) being re-hired by the same gig firm, *ii*) finding a job in another gig firm, *iii*) finding a job in a traditional firm, or *iv*) becoming unemployed. The gig workers who are not re-hired search for other gig and traditional jobs, and if a match is formed, they begin their new job without delay. Gig workers who are not re-hired and do not form another match at the beginning of the period become unemployed and would not be eligible for employment until the next period.

In contrast, jobs at traditional firms are more secure and matches typically have a longer duration. At the beginning of each period, some job matches at traditional firms break down and the separated workers become unemployed. These newly separated traditional workers are not eligible for employment until the following period. Some matches at traditional firms survive but end because the workers find jobs in the gig sector. Other matches survive and the workers enter the next period employed in the same firm. Fig 4.1) summarises the job search and worker flows in the model.

At the beginning of each period, gig firms post vacancies which they aim to fill by re-hiring some of their past workers, and new workers from other gig firms and traditional firms. Workers in gig work are re-hired by the same firm with probability rh^g. Gig workers search for new gig jobs bearing in mind the probability of not being re-hired in the same firm; their search is given by $s_t^{g,g} = (1 - rh^g)\zeta^{g,g} n_t^g$. Unemployed workers search for gig jobs $s_t^{g,u} = \zeta^{g,u} u_t$ and workers in traditional jobs search for gig jobs $s_t^{g,tr} = (1 - \tau^{tr})\zeta^{g,tr} n_t^{tr}$. This means that search for gig jobs is

$$s_t^g = s_t^{g,g} + s_t^{g,u} + s_t^{g,tr} \tag{4.2}$$

where τ^{tr} is the traditional job destruction rate, $\zeta^{g,g}$, $\zeta^{g,u}$ and $\zeta^{g,tr}$ are the search intensities which I define as the effort, frequency and scope of workers search for work intended to increase their probability of finding a job match (Khele et al. (2018), Pissarides (1984)). I assume that search intensity is constant, following Moscarini and Postel-Vinay (2016) and Moscarini and Postel-Vinay (2018*a*).[21]

Similarly, traditional firms post vacancies at the beginning of each period and aim to fill them with workers from the gig sector and the unemployed. So search for traditional jobs by unemployed workers is $s_t^{tr,u} = \zeta^{tr,u} u_t$, and for workers in the gig sector, search for a traditional job is $s_t^{tr,g} = (1 - rh^g)\zeta^{tr,g} n_t^g$,[22]

[21] There are many different categories of search in this model; I assume fixed search intensity for simplicity. Gertler et al. (2020*b*) and Krause and Lubik (2006) assume fixed and variable search intensities for unemployed and on-the-job worker search respectively. See also DeLoach and Kurt (2013) and Shimer (2004) for empirical evidence of the (a)cyclicality of search intensity.

[22] The data shows that of the workers who remained in traditional work between 2019Q3 and 2019Q4, only about 2% changed employers. This suggests very small within-sector traditional job-to-job movements, so I do not model this

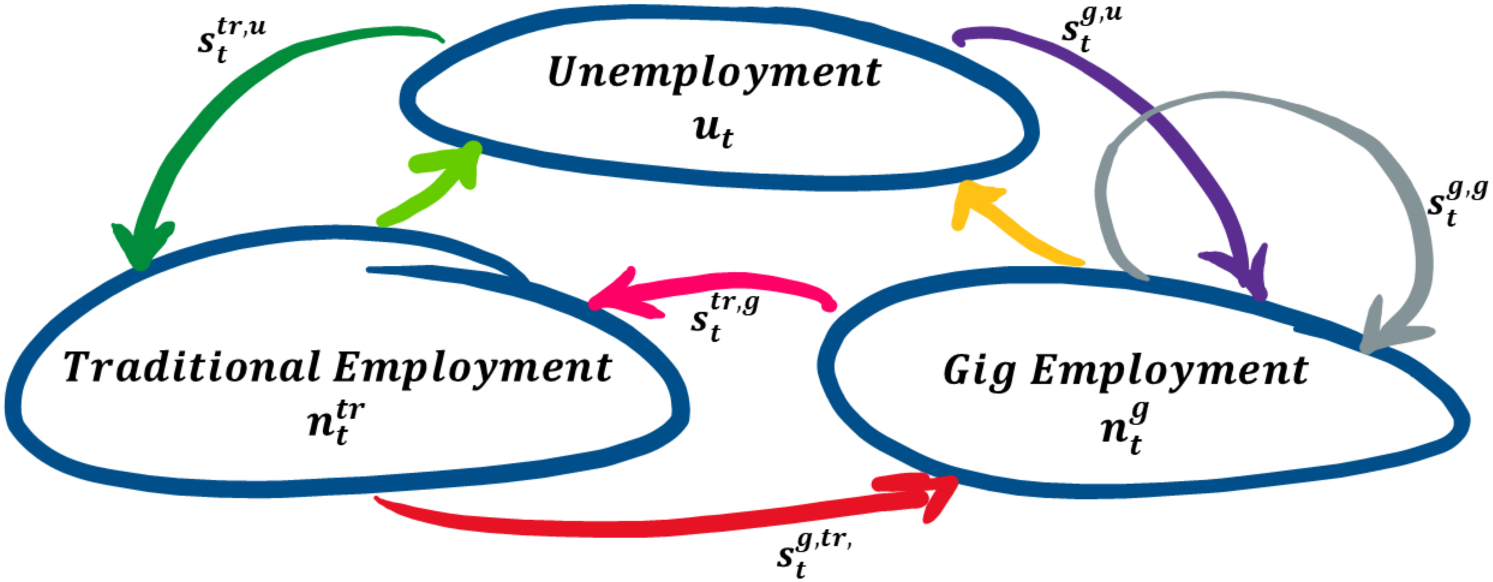

Figure 4.1: UK Gig and Traditional Sector Labour Market Flows
The figure shows 7 distinct movements of workers in the UK between traditional and gig employment. The data shows that workers search for gig or traditional work jobs as a stepping stone to, or when unable to find alternative employment, when facing redundancy or retirement, to meet a demand in the market, due to illness, disability or full-time education, and so on. Also, within-sector gig job search may be for idiosyncratic reasons, for example, when facing difficulties at work, for proximity workplace to home, relocation, etc.

where $\zeta^{tr,u}$ and $\zeta^{tr,g}$ are the search intensities. So

$$s_t^{tr} = s_t^{tr,u} + s_t^{tr,g} \tag{4.3}$$

All new matches become productive immediately. The matching functions for wholesale traditional and gig firms respectively are

$$h_t^{tr} = m^{tr}(v_t^{tr})^{\alpha_{tr}}(s_t^{tr})^{1-\alpha_{tr}} \tag{4.4}$$

and

$$h_t^{g} = m^{g}(v_t^{g})^{\alpha_{g}}(s_t^{g})^{1-\alpha_{g}} \tag{4.5}$$

v_t^{tr} and v_t^g are the number of vacancies posted by traditional and gig firms, m^{tr} and m^g are the matching technologies. Market tightness in each sector is

$$\theta_t^{tr} = \frac{v_t^{tr}}{s_t^{tr}} \tag{4.6}$$

and

$$\theta_t^{g} = \frac{v_t^{g}}{s_t^{g}} \tag{4.7}$$

the vacancy-filling rates are $q_t^{tr} = \frac{h_t^{tr}}{v_t^{tr}}$ and $q_t^g = \frac{h_t^g}{v_t^g}$, while the job-finding rates are $f_t^{tr} = \frac{h_t^{tr}}{s_t^{tr}}$ and $f_t^g = \frac{h_t^g}{s_t^g}$.

Given that the rate at which workers find jobs depends on their search intensity, unemployed workers find traditional jobs at the rate $f_t^{tr,u} = \frac{s_t^{tr,u}}{s_t^{tr}}\frac{h_t^{tr}}{u_t}$, so

$$f_t^{tr,u} = \zeta^{tr,u} f_t^{tr} \tag{4.8}$$

Similarly, the unemployment-gig job-finding rate is

$$f_t^{g,u} = \zeta^{g,u} f_t^{g} \tag{4.9}$$

and in the same way, the traditional-gig, gig-traditional and gig-gig job-finding rates are $f_t^{tr,g} = (1 - rh^g)\zeta^{tr,g} f_t^{tr}$, $f_t^{g,tr} = (1-\tau^{tr})\zeta^{g,tr} f_t^g$ and $f_t^{g,g} = (1 - rh^g)\zeta^{g,g} f_t^g$ respectively.

4.3 The Household

The household has the utility function

$$H_t = E_t \sum_{k=0}^{\infty} \beta^{t+k} e^{\varepsilon_{t+k}^d} \frac{C_{t+k}^{1-\eta}}{1-\eta} \tag{4.10}$$

and the budget constraint

$$P_t w_t^g n_t^g + P_t w_t^{tr} n_t^{tr} + P_t b u_t + \Pi_t + B_{t-1} = C_t + P^b B_t \tag{4.11}$$

where P is the price index, P^b is the nominal price of bonds, b is unemployment benefit, Π is the dividend recieved from the ownership of firms and C is household consumption, $e^{\varepsilon_t^d}$ is a preference shock, $\varepsilon_t^d = \rho_d \varepsilon_{t-1}^d + \varrho_t^d$, $0 \leq \rho_d \leq 1$ and ϱ_t^d is distributed as $N(0, \sigma_d^2)$. The wage for traditional employment is w^{tr} and the gig sector wage is w^g.

transition.

The household maximises utility subject to their budget constraint, choosing consumption and bond purchases to give the Euler equation

$$C_t^{-\eta} = \beta e^{\varepsilon_t^d} E_t C_{t+1}^{-\eta} \frac{1+i_t}{1+E_t\pi_{t+1}} \tag{4.12}$$

Given that the real interest rate is $r_t = \frac{1+i_t}{1+E_t\pi_{t+1}}$, the stochastic discount factor is

$$E_t\beta_{t,t+1} = \beta e^{\varepsilon_t^d} \frac{E_t C_{t+1}^{-\eta}}{C_t^{-\eta}} \tag{4.13}$$

The household consumes retail goods from the traditional and gig sectors. I assume

$$C_t = \Big[(\Gamma^{tr})^{\frac{1}{\nu}}(C_t^{tr})^{\frac{\nu-1}{\nu}} + (1-\Gamma^{tr})^{\frac{1}{\nu}}(C_t^{g})^{\frac{\nu-1}{\nu}}\Big]^{\frac{1}{\nu-1}} \tag{4.14}$$

where C^{tr} is consumption of traditional retail goods, C^g is consumption of gig retail goods, ν is the elasticity of substitution between both types of good and Γ^{tr} is the share of household consumption that is made up of traditional retail goods. The corresponding price index is

$$P_t = \Big[(\Gamma^{tr})(P_t^{tr})^{1-\nu} + (1-\Gamma^{tr})(P_t^{g})^{1-\nu}\Big]^{\frac{1}{1-\nu}} \tag{4.15}$$

where P_t^{tr} and P_t^g are the price indexes for traditional and gig retail goods respectively, so the demand for retail goods from each sector is

$$C_t^{tr} = (\Gamma^{tr})\Big(\frac{P_t^{tr}}{P_t}\Big)^{-\nu} C_t \tag{4.16}$$

and

$$C_t^{g} = (1-\Gamma^{tr})\Big(\frac{P_t^{g}}{P_t}\Big)^{-\nu} C_t \tag{4.17}$$

The household consumes a bundle of goods from each sector. Consumption of traditional retail goods is $C_t^{tr} = (\int_0^1 (C_{jt}^{tr})^{\frac{\nu^{tr}-1}{\nu^{tr}}} dj)^{\frac{\nu^{tr}}{\nu^{tr}-1}}$ and the price index is $P_t^{tr} = (\int_0^1 (P_{jt}^{tr})^{(1-\nu^{tr})} dj)^{\frac{1}{1-\nu^{tr}}}$ where C_j^{tr} is household consumptionof traditional good j and P_j^{tr} is the price of good j. Similarly, household consumption of gig retail goods is $C_t^{g} = (\int_0^1 (C_{jt}^{g})^{\frac{\nu^{g}-1}{\nu^{g}}} dj)^{\frac{\nu^{g}}{\nu^{g}-1}}$, with the price index is $P_t^{g} = (\int_0^1 (P_{jt}^{g})^{(1-\nu^{g})} dj)^{\frac{1}{1-\nu^{g}}}$ where C_j^g is household consumption of gig retail good j and P_j^g is the price of gig retail good j. These imply the household demand for each retail traditional good is

$$C_{jt}^{tr} = \Big(\frac{P_{jt}^{tr}}{P_t^{tr}}\Big)^{-\nu^{tr}} C_t^{tr} \tag{4.18}$$

and the demand for each gig good is

$$C_{jt}^{g} = \Big(\frac{P_{jt}^{g}}{P_t^{g}}\Big)^{-\nu^{g}} C_t^{g} \tag{4.19}$$

4.4 Wholesale Firms

I assume that all traditional wholesale firms are identical and all gig wholesale firms are identical. Traditional wholesale firms produce intermediate goods which are sold to traditional retail firms in a perfectly competitive market. Likewise, gig wholesale firms produce intermediate goods which they sell to gig retail firms in a perfectly competitive market. Wholesale firms post vacancies and hire workers to produce intermediate goods.

4.4.1 Traditional Wholesale Firms

The representative traditional firm has the profit function

$$J_t^{tr} = E_t \sum_{k=0}^{\infty} \beta_{t,t+1} \Big\{ \frac{P_t^{tr,W}}{P_t^{tr}} Y_{t+k}^{tr,W} - w_{t+k}^{tr} n_{t+k}^{tr} - \gamma^{tr} v_{t+k}^{tr} \Big\} \tag{4.20}$$

where $P_t^{tr,W}$ is the nominal price of the traditional wholesale good, Y^{tr} is the output produced by the traditional firm, γ^{tr} is the cost of posting a vacancy in the traditional sector and v^{tr} is the number of vacancies posted by the traditional firm. The production function is

$$Y_t^{tr,W} = A_t^{tr} n_t^{tr} \tag{4.21}$$

where $A_t^{tr} = A^{tr} e^{\varepsilon_t^{s^{tr}}}$. $e^{\varepsilon_t^{s^{tr}}}$ is a shock to the productivity of workers at high productivity firms, $\varepsilon_t^{s^{tr}} = \rho_{s^{tr}} \varepsilon_{t-1}^{s^{tr}} + \varrho_t^{s^{tr}}$, $0 \leq \rho_{s^{tr}} \leq 1$ and $\varrho_t^{s^{tr}}$ is distributed as $N(0, \sigma_{s^{tr}}^2)$.

The traditional firm uses technology that requires only inflexible labour input. The evolution of employment in each firm is

$$n^{tr} = \rho_t^{tr} n_{t-1}^{tr} + q_t^{tr} v_t^{tr} \tag{4.22}$$

where $\rho_t^{tr} = 1 - \tau^{tr} - f_t^{g,tr}$ is the probability that the match survives and the workers do not move to the gig sector.

The traditional firm maximises profits choosing the number of vacancies to post to obtain

$$\frac{\partial J_t^{tr}}{\partial v_t^{tr}} = -\gamma^{tr} + \chi_t^{tr} q_t^{tr} = 0 \tag{4.23}$$

where χ^{tr} is the Lagrangian multiplier. Choosing the number of workers

$$\frac{\partial J_t^{tr}}{\partial n_t^{tr}} = \frac{P_t^{tr,W}}{P_t^{tr}} A_t^{tr} - w_t^{tr} + E_t \beta_{t,t+1} \rho_{t+1}^{tr} \chi_{t+1}^{tr} - \chi_t^{tr} = 0 \tag{4.24}$$

Combining (4.23) and (4.24), the optimality condition for the traditional firm is

$$\lambda_t^{tr} = \frac{A_t^{tr}}{\mu_t^{tr}} - w_t^{tr} \tag{4.25}$$

where the markup of the traditional retail firm $\mu_t^{tr} = \frac{P_t^{tr}}{P_t^{tr,W}}$ and $\lambda_t^{tr} = \gamma^{tr} (\frac{1}{q_t^{tr}} - E_t \beta_{t,t+1} \rho_{t+1}^{tr} \frac{1}{q_{t+1}^{tr}})$ is the marginal hiring cost of a traditional worker.

4.4.2 Gig Wholesale Firms

The gig wholesale firm uses technology that requires flexible labour input and has the profit function

$$J_t^{g} = \sum_{k=0}^{\infty} \beta_{t,t+1} \Big\{ \frac{P_t^{g,W}}{P_t^{g}} Y_{t+k}^{g,W} - w_{t+k}^{g} n_{t+k}^{g} - \gamma^{g} v_{t+k}^{g} \Big\} \tag{4.26}$$

subject to the production function is

$$Y_t^{g,W} = A_t^{g} n_t^{g} \tag{4.27}$$

where $A_t^{g} = A^{g} e^{\varepsilon_t^{s^{g}}}$, $\varepsilon_t^{s^{g}}$ is a shock to the productivity of workers at low productivity firms, $\varepsilon_t^{s^{g}} = \rho_{s^{g}} \varepsilon_{t-1}^{s^{g}} + \varrho_t^{s^{g}}$, $0 \leq \rho_{s^{g}} \leq 1$ and $\varrho_t^{s^{g}}$ is distributed as $N(0, \sigma_{s^{g}}^2)$. The evolution of employment of workers in the gig firm is

$$n_t^{g} = \rho_t^{g} n_{t-1}^{g} + q_t^{g} v_t^{g} \tag{4.28}$$

where $\rho_t^g = rh^g$. For the sector, $\rho_t^g = rh^g + (1 - rh^g)f_t^{g,g}$.

Similar to the traditional wholesale firm, the gig firm maximises profits choosing the number of workers and vacancies to obtain the optimality condition

$$\lambda_t^g = \frac{A_t^g}{\mu_t^g} - w_t^g \tag{4.29}$$

where the markup of the gig retail firm is $\mu_t^g = \frac{P_t^g}{P_t^{g,W}}$ and $\lambda_t^g = \gamma^g(\frac{1}{q_t^g} - E_t\beta_{t,t+1}\rho_{t+1}^g\frac{1}{q_{t+1}^g})$ is the marginal hiring cost of workers in the gig sector.

4.5 The Wage

All workers in traditional employment earn the same wage and all workers in gig employment earn the same wage. The wage in each sector is determined by a Nash bargain between firms and workers in their respective sectors

4.5.1 The Surplus

The household derives utility when a worker is in traditional employment. At the same time, for each worker in traditional employment, the opportunity cost to the household is one less gig and unemployed worker. This implies that the household surplus for an additional worker in traditional employment is

$$S_t^{tr} = \frac{1}{C_t^{-\eta}}\left(\frac{\partial H_t}{\partial n_t^{tr}} - \frac{\partial H_t}{\partial u_t}\right) \tag{4.30}$$

Where $\frac{\partial H_t}{\partial n_t^{tr}} = C_t^{-\eta}w_t^{tr} + \beta_t E_t \rho_{t+1}^{tr}\frac{\partial H_{t+1}}{\partial n_{t+1}^{tr}}$ and $\frac{\partial H_t}{\partial u_t} = C_t^{-\eta}b + \beta_t E_t\left(f_{t+1}^{tr,u}\frac{\partial H_{t+1}}{\partial n_{t+1}^{tr}} + f_{t+1}^{g,u}\frac{\partial H_{t+1}}{\partial n_{t+1}^{g}}\right)$,

$$S_t^{tr} = w_t^{tr} - b + (\rho_{t+1}^{tr} - f_{t+1}^{tr,u})\beta_{t,t+1}S_{t+1}^{tr} - f_{t+1}^{g,u}S_{t+1}^g \tag{4.31}$$

where $\beta_t = \beta e^{\varepsilon_{t+k}^d}$ and $\beta_{t,t+1}$ is the stochastic discount factor in (4.13). The surplus to the household for an additional worker in gig employment is

$$S_t^g = w_t^g - b + (\rho_{t+1}^g - f_{t+1}^{g,u})\beta_{t,t+1}S_{t+1}^g - f_{t+1}^{tr,u}S_{t+1}^{tr} \tag{4.32}$$

S_t^{tr} and S_t^g imply that for an additional worker in traditional or gig employment, the household receives a wage but not benefits, as the worker is no longer unemployed. The household also receives expected utility from the continuation of the new job match, but loses some utility as the worker the will not search for work in either sector in the next period.

The value of an additional worker to the traditional firm is $F_t^{tr} = \frac{\partial J_t^{tr}}{\partial n_t^{tr}}$, which gives

$$F_t^{tr} = A_t^{tr} - w_t^{tr} + \beta_{t,t+1}E_t\rho_{t+1}^{tr}F_{t+1}^{tr} \tag{4.33}$$

For the gig firm, the surplus is $F_t^g = \frac{\partial J_t^g}{\partial n_t^g}$, which gives

$$F_t^g = A_t^g - w_t^g + \beta_{t,t+1}E_t\rho_{t+1}^g F_{t+1}^g \tag{4.34}$$

4.5.2 The Wage Bargain

The household and the traditional firm maximise $(F_t^{tr})^{\vartheta^{tr}}(S_t^{tr})^{(1-\vartheta^{tr})}$ choosing the wage to obtain the sharing rule

$$(1-\vartheta^{tr})F_t^{tr} = \vartheta^{tr} S_t^{tr} \tag{4.35}$$

where ϑ^{tr} is the bargaining power of workers in the traditional sector. Substituting (4.31) and (4.33) into the sharing rule gives the traditional sector wage

$$w_t^{tr} = (1-\vartheta^{tr})\Big[A_t^{tr} + \gamma^{tr}\zeta^{tr,u}\beta_{t,t+1}E_t\theta_{t+1}^{tr} + \gamma^g\zeta^{g,u}\beta_{t,t+1}E_t\theta_{t+1}^{g}\Big] + \vartheta^{tr}b \tag{4.36}$$

and similarly, the gig sector wage is

$$w_t^{g} = (1-\vartheta^{g})\Big[A_t^{g} + \gamma^{tr}\zeta^{tr,u}\beta_{t,t+1}E_t\theta_{t+1}^{tr} + \gamma^g\zeta^{g,u}\beta_{t,t+1}E_t\theta_{t+1}^{g}\Big] + \vartheta^{g}b \tag{4.37}$$

Following the evidence that the bargaining power and productivity in the gig sector are lower than in the traditional sector, the gig wage is lower than the traditional wage. This explains the evidence that workers in gig employment earn lower wages than the same type of worker in the same type of job in the traditional sector.[23]

Market tightness reflects the difficulty with which firms replace their workers. The model shows that market tightness in each sector positively impacts the wage in the same sector, and in addition, market tightness in one sector directly impacts the wage in the other sector. Given that workers can find employment in the other sector to substitute for employment in one sector, gig work is an outside option for workers in traditional employment and vice versa for workers in gig employment. When gig market tightness is high, the value of traditional workers' outside option is high, and by extension, the traditional workers' value to the traditional firm is high. This results in a higher traditional sector wage. Conversely, when gig market tightness is low, the value of the traditional worker's outside option falls, which means a relatively lower traditional wage. The same applies to workers in the gig sector and the gig wage.

The relevance of gig and traditional market tightness in both (4.37) and (4.36) is that poor labour market conditions in one sector can lead to relatively low wages in both sectors and a lower average wage. In particular, the wage equations suggest that if the traditional sector is thriving alongside a waning gig sector, the gig sector wage might be improved by the good condition of the traditional sector, but the traditional wage might be lowered by the weak gig sector. The reverse would apply to a thriving gig sector alongside a weak traditional sector. Furthermore, if labour market conditions are poor in both sectors, the wage in both sectors would be even lower. This offers insight into the role of the gig economy in wage growth in the UK.

4.6 Retail Firms

I assume that traditional retail firms are identical. They purchase intermediate goods from traditional wholesale firms to costlessly produce differentiated finished traditional goods. Finished traditional goods are sold to households in a monopolistically competitive market, so I assume $Y_t^{tr} = C_t^{tr}$. Gig retail firms are also identical, purchase intermediate wholesale gig goods, costlessly produce differentiated finished

[23] It is worth noting that an alternative explanation for wage dispersion and slow wage growth associated with the gig economy in the literature is that there are nonpecuniary benefits from gig work which make the wage for gig work comparatively low. Or put differently, traditional work requires a premium to offset the nonpecuniary benefits of gig work, which makes the traditional wage higher than the gig wage. See the Rosen (1986) theory for equalisaing wage differentials.

gig goods that are sold to households in a monopolistically competitive market, so $Y_t^g = C_t^g$.

The traditional retail firm maximises profits choosing the price P_t^{tr} in the function

$$E_t \sum_{k=0}^{\infty} (\omega^{tr})^k \Big\{ \beta_{t,t+k} \Big(\frac{P_t^{tr} - P_{t+k}^{tr,W}}{P_{t+k}^{tr}} \Big) Y_{t+k}^{tr} \Big\} \tag{4.38}$$

subject to household demand

$$Y_t^{tr} = \Big(\frac{P_t^{tr}}{P_t^{tr}} \Big)^{-\nu^{tr}} Y_t^{tr} \tag{4.39}$$

and the production function

$$Y_t^{tr} = Y_t^{tr,W} \tag{4.40}$$

where $Y^{tr,W}$ is the amount of traditional wholesale goods purchased by the traditional retail firm, Y_t^{tr} is the output of the traditional retail firm and ω^{tr} is the probability that the firm is unable to reset its price in future periods. This gives the optimal price of the finished traditional good

$$\frac{P_t^{*tr}}{P_t^{tr}} = \mu^{tr}(1 - \beta\omega^{tr}) E_t \sum_{k=0}^{\infty} (\omega^{tr})^k \beta_{t,t+k} mc_{t+k}^{tr} \tag{4.41}$$

The traditional firm sets its price as a markup on the marginal cost where the marginal cost $mc_{t+k}^{tr} = \frac{P_t^{tr,W}}{P_{t+k}^{tr}}$ is the price of the intermediate traditional good and $\mu^{tr} = \frac{\nu^{tr}}{\nu^{tr}-1}$ is the markup.

Using the same logic, the optimal price of the finished gig good is

$$\frac{P_t^{*g}}{P_t^{g}} = \mu^{g}(1 - \beta\omega^{g}) E_t \sum_{k=0}^{\infty} (\omega^{g})^k \beta_{t,t+k} mc_{t+k}^{g} \tag{4.42}$$

I assume that the traditional retail good is similar but superior to the gig retail good because traditional wholesale firms use better production technology. However, the price of the gig retail good is lower than the traditional retail good given that the cost of hiring workers and the wage in the gig sector are low, the price of the intermediate gig good is low $\frac{P_t^{g,W}}{P_t^g} < \frac{P_t^{tr,W}}{P_t^{tr}}$ and the gig retail marginal cost is low $mc_{t+k}^g < mc_{t+k}^{tr}$. So the gig sector receives its share of aggregate demand by offering the household a cheap alternative to traditional retail goods.

Firms in the traditional retail sector follow the price-setting rule

$$P_t^{tr} = (1 - \omega^{tr}) P_t^{*tr} + \omega^{tr} P_{t-1}^{tr} \tag{4.43}$$

where $(1 - \omega^{tr})$ firms reset their price in period t, ω^{tr} firms are unable to reset their price retain their past price. Taking the log deviation of (4.41) and (4.43) around a zero inflation steady state gives

$$\pi_t^{tr} = \kappa^{tr} \widehat{mc}_t^{tr} + \beta \pi_{t+1}^{tr} \tag{4.44}$$

This is the Phillips Curve for the traditional sector with the slope $\kappa^{tr} = \frac{(1-\omega^{tr})(1-\beta\omega^{tr})}{\omega^{tr}}$. In the same way, the Phillips Curve for the gig sector is

$$\pi_t^{g} = \kappa^{g} \widehat{mc}_t^{g} + \beta \pi_{t+1}^{g} \tag{4.45}$$

where $\kappa^{g} = \frac{(1-\omega^{g})(1-\beta\omega^{g})}{\omega^{g}}$ is the slope.

4.7 Monetary Policy

I assume that the interest rate is set following the Taylor rule

$$i_t = \bar{i} + \phi_\pi \pi_t + \phi_y (y_t - y) + \varepsilon_t^i \tag{4.46}$$

where ϕ_π and ϕ_y are the monetary policy responses to inflation and output, ε_t^i is a monetary policy shock.

4.8 Calibration

I used 2019 third and fourth quarter Labour Force Survey data to derive labour market calibration targets. I excluded the under-16 and economically inactive respondents in both quarters,[24] leaving $21,909$ cases which made up the sample. Of the $21,909$ workers in the sample, in Q3, $21,231$ were employed while the remaining 678 were unemployed. This implies $n = 0.969$ and $u = 0.031$.

I have categorised gig and traditional workers based on their reported main job and I do not consider second jobs. This does not impact the classification of workers and their rates of transition between sectors, but it suggests that the size of UK gig economy might be understated. I identified workers in traditional employment by the employees in permanent jobs, the self-employed who employ other workers and the lone-working self-employed whose hours do not vary. I identified workers in gig employment by employees whose jobs were not permanent, including respondents who were working for an employment agency, in casual or seasonal work, under contract for a fixed period or fixed task and any other reason for not being permanent, and the lone-working self-employed whose work hours vary. From these, I determined that the number of workers in traditional employment is $18,236$, the number of workers in gig work is $2,995$ and therefore, $n^{tr} = 0.832$ and $n^g = 0.137$.

Following each respondent from Q3 to Q4, I tracked the changes in their employment status and type to derive job transition rates. Of the 678 workers who were unemployed in Q3, 566 became employed in traditional jobs in Q4, so $\frac{566}{678}$ gives the unemployment-to-traditional job-finding rate $f^{tr,u} = 0.8348$. Similarly, 96 of the Q3 unemployed workers became employed in gig work in Q4, so the unemployment-to-gig job-finding rate $f^{g,u} = 0.1416$.

On job-to-job transition, of the $2,995$ workers in gig employment in Q3, 353 workers remained in gig work with the same employer in Q4; I assume that these worker's contracts were renewed, so $\frac{353}{2{,}995}$ gives the gig re-hiring rate $rh^g = 0.1179$. Between Q3 and Q4, $2,462$ of the $2,995$ gig workers transitioned to traditional employment, this implies that the rate at which gig workers find traditional jobs given that they are not re-hired by the same gig firm is $(1 - rh^g) f^{tr,g} = 0.8220$, which means the the gig-to-traditional job-finding rate $f^{tr,g} = 0.9319$. There were 17 workers in gig work in Q3 who remained in gig work but changed employers; this implies $(1 - rh^g) f^{g,g} = 0.0057$ and the gig-gig job transition rate $f^{g,g} = 0.0064$. Between Q3 and Q4, $2,536$ traditional workers moved to gig employment, so $\frac{2{,}536}{18{,}236}$ gives the traditional-to-gig job-finding rate $f^{g,tr} = 0.1391$. Also, between Q3 and Q4, $15,168$ traditional workers remained in traditional employment; I assume that their match continues, so $\frac{15{,}168}{18{,}236}$ gives the traditional job continuation rate $\rho^{tr} = 0.8318$.

To better match the calibration targets, I set the coefficient of relative risk aversion $\eta = 0.73$, the monetary policy response to inflation and output respectively $\phi_\pi = 1.48$ and $\phi_y = 0.31$, employment opportunity cost $b = 0.58$ and the matching elasticities $\alpha_{tr} = \alpha_g = 0.3$. There is evidence that hiring traditional workers is costlier than hiring gig workers and gig jobs are highly fragmented so gig firms and workers face fewer challenges with search and matching. Given the relatively higher traditional sector

[24] I do not model entry and exit from the labour force.

recruitment cost, traditional firms need to have a sufficient number of tasks to be done before deciding to recruit a worker which implies that workers would need to have a range of skills to fit traditional job openings. This means that traditional sector search and matching takes more time and effort (Gomez-Herrera et al. (2017)). Following this evidence and the rising use of online and app-based platforms,[25] mobile devices and gadgets, I assume higher matching efficiency and lower cost of posting vacancies in the gig sector and I set $\gamma^g = 0.3$, $\gamma^{tr} = 0.33$, $m^{tr} = 0.8$ and $m^g = 1$. I also assume $A^{tr} = 1.5$, $A^g = 0.8$, $\vartheta^{tr} = 0.51$ and $\vartheta^g = 0.41$ reflecting the relatively low productivity and bargaining power in the gig sector.

Table 4.1: Calibration Targets

Parameter	Label	Target	Source	This Model
n^g	Workers in Gig Employment	0.137	LFS	0.1370
n^{tr}	Workers in Traditional Employment	0.832	LFS	0.8320
u	Unemployment	0.031	LFS	0.0310
$f^{tr,u}$	Unemployment-Traditional Job-Finding Rate	0.8348	LFS	0.8341
$f^{tr,g}$	Gig-Traditional Job-Finding Rate	0.9319	LFS	0.9319
$f^{g,u}$	Unemployment-Gig Job-Finding Rate	0.1416	LFS	0.1414
$f^{g,tr}$	Traditional-Gig Job-Finding Rate	0.1391	LFS	0.1393
$f^{g,g}$	Gig-Gig Job-Finding Rate	0.0064	LFS	0.0064
rh^g	Gig Re-hiring Rate	0.1179	LFS	0.1179
τ^{tr}	Traditional Job Destruction Rate	0.0292	LFS	0.04
ρ^{tr}	Traditional Job Continuation Rate	0.8318	LFS	0.8207

Table 4.2: Calibrated Parameters

Parameter	Label	Value	Source
r	Real Interest Rate	0.0101	Faccini et. al (2013)
η	Coefficient of Relative Risk Aversion	0.73	Faccini et al (2013)
b	Unemployment Benefit	0.58	Faccini et. al (2013)
ν^{tr}	Traditional Goods Elasticity of Demand	11	Faccini et al (2013)
ν^g	Gig Goods Elasticity of Demand	11	Faccini et al (2013)
ν	Aggregate Demand Price Elasticity	11	Faccini et al (2013)
α_{tr}	Traditional Sector Vacancy-Matching Elasticity	0.3	Faccini et. al (2013)
α_g	Gig Sector Vacancy-Matching Elasticity	0.3	Faccini et. al (2013)
m^{tr}	Traditional Sector Matching Efficiency	0.8	Author's calculation
m^g	Gig Sector Matching Efficiency	1	Author's calculation
ϑ^{tr}	Traditional Sector Bargaining Power	0.51	Author's calculation
ϑ^g	Gig Sector Bargaining Power	0.41	Author's calculation
γ^{tr}	Traditional Sector Vacancy Cost	0.33	Author's calculation
γ^g	Gig Sector Vacancy Cost	0.03	Author's calculation
$\zeta^{tr,u}$	Unemployment-Traditional Job Search Intensity	0.777	Author's calculation
$\zeta^{tr,g}$	Gig-Traditional Job Search Intensity	8.681	Author's calculation

continued ...

[25] eg. Etsy, Amazon Mechanical Turk, TaskRabbit, Udemy, Facebook Marketplace, Airbnb, Uber, Deliveroo.

...continued

Parameter	Label	Value	Source
$\zeta^{g,u}$	Unemployment-Gig Job Search Intensity	0.32	Author's calculation
$\zeta^{g,g}$	Gig-Gig Job Search Intensity	0.145	Author's calculation
$\zeta^{g,tr}$	Traditional-Gig Job Search Intensity	0.3283	Author's calculation
κ^{tr}	Slope of Traditional Sector PC	0.1	OBR
κ^{g}	Slope of Gig Sector PC	0.1	Author's calculation
A^{tr}	Traditional Sector Productivity	1.5	Author's calculation
A^{g}	Gig Sector Productivity	0.8	Author's calculation
$\bar{i}$	Inflation Target	0.02	OBR
ϕ_{π}	Monetary Policy Response to Inflation	1.48	Faccini et al (2013)
ϕ_{y}	Monetary Policy Response to Output	0.31	Faccini et al (2013)

4.9 Results

Firms respond to a positive aggregate demand shock by increasing output. To do this, firms create vacancies and hire more workers, employment increases and unemployment falls. Due to the economic expansion, Fig. 4.2) shows that workers who are in gig employment flow into the traditional sector to the disadvantage of the unemployed. Since the traditional sector is significantly larger than the gig sector, the traditional sector would account for a larger share of the additional output resulting from the demand shock. This explains the large movement of workers from gig work to traditional employment and the contraction of the gig sector as discussed earlier in this chapter. Gig employment falls but unemployment also falls because of gig workers transitioning to traditional employment. Traditional sector employment increases and the overall impact of the demand shock on employment is positive.

The result in Fig. 4.2) suggests that *i*) a large number of workers hold gig jobs until there is an opportunity to transition to traditional work, *ii*) the muted increase in total employment compared to the sharp fall in unemployment suggests that the fall in unemployment is more from the *reshuffling* of employed workers who otherwise might have become unemployed, than from the hiring of presently unemployed workers, and *iii*) if there are fewer unemployed workers searching for work than those searching on the job, there is less likelihood for the unemployed to find work, therefore, job-to-job transitions might reduce employment-to-unemployment transition, but would also reduce transition from unemployment into employment.

An aggregate supply shock has a similar impact, but there is a larger increase in aggregate and sectoral output than is the case with an aggregate demand shock. The results are shown in Fig. 4.3).

Traditional and gig sector productivity shocks are shown in Figs. 4.4) and 4.5) respectively. A productivity shock in one sector impacts both sectors. A traditional sector productivity shock creates an expansion in the traditional sector that induces a transition of workers from gig to traditional employment, but there is also hiring from unemployment into the traditional sector. The gig sector contracts as workers move from gig to traditional employment, but recovers as the workers remaining in the gig sector, workers hired from the traditional sector and the unemployed fill in the jobs left behind by the workers who made the gig-to-traditional employment transition.

As the gig sector is considerably smaller than the traditional sector, a gig sector productivity shock does not have the same impact as a traditional sector productivity shock. Gig employment increases; this comes from workers remaining in the gig sector, moving from one gig job to another, and workers in

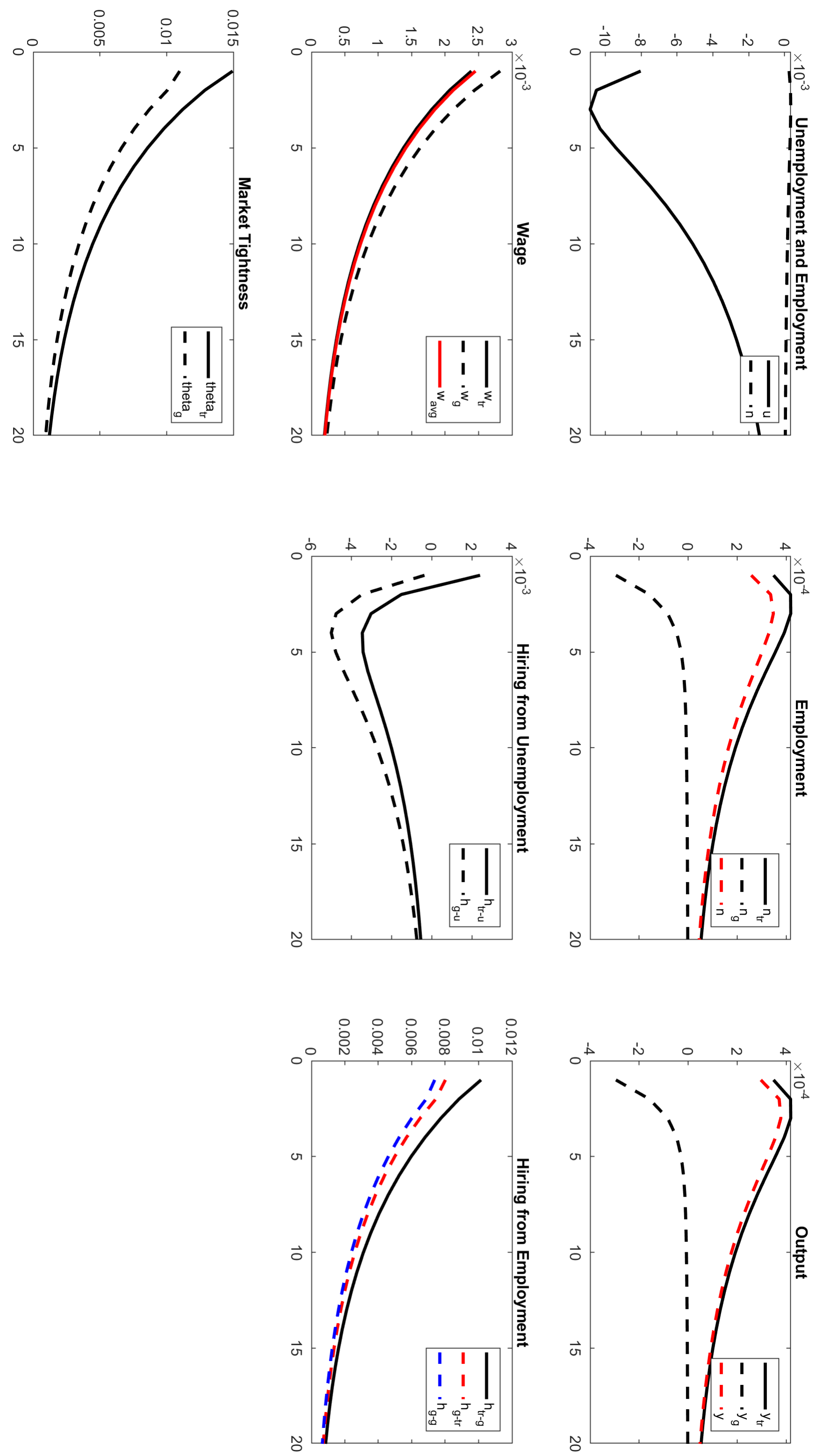

Figure 4.2: An Aggregate Demand Shock

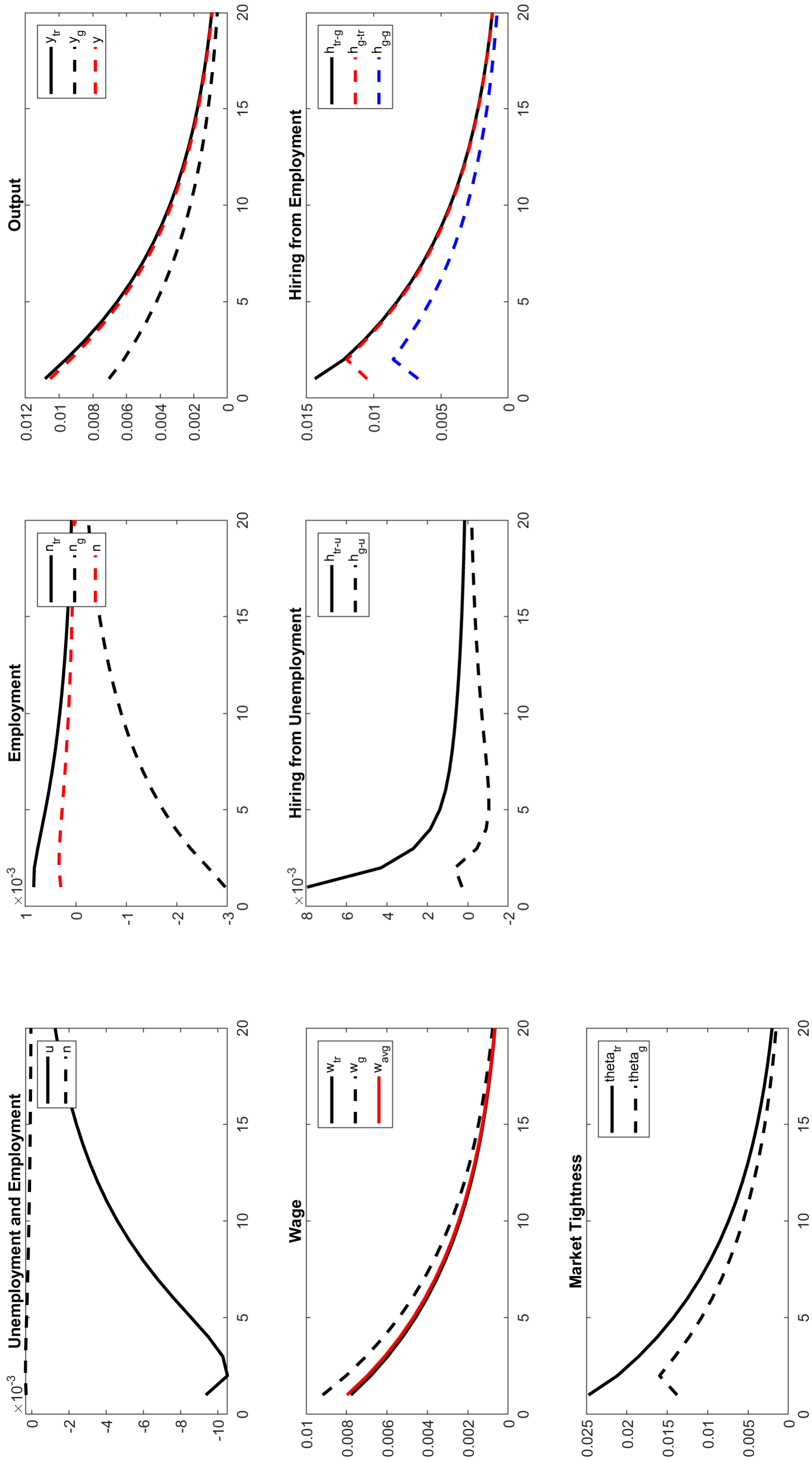

Figure 4.3: An Aggregate Supply Shock

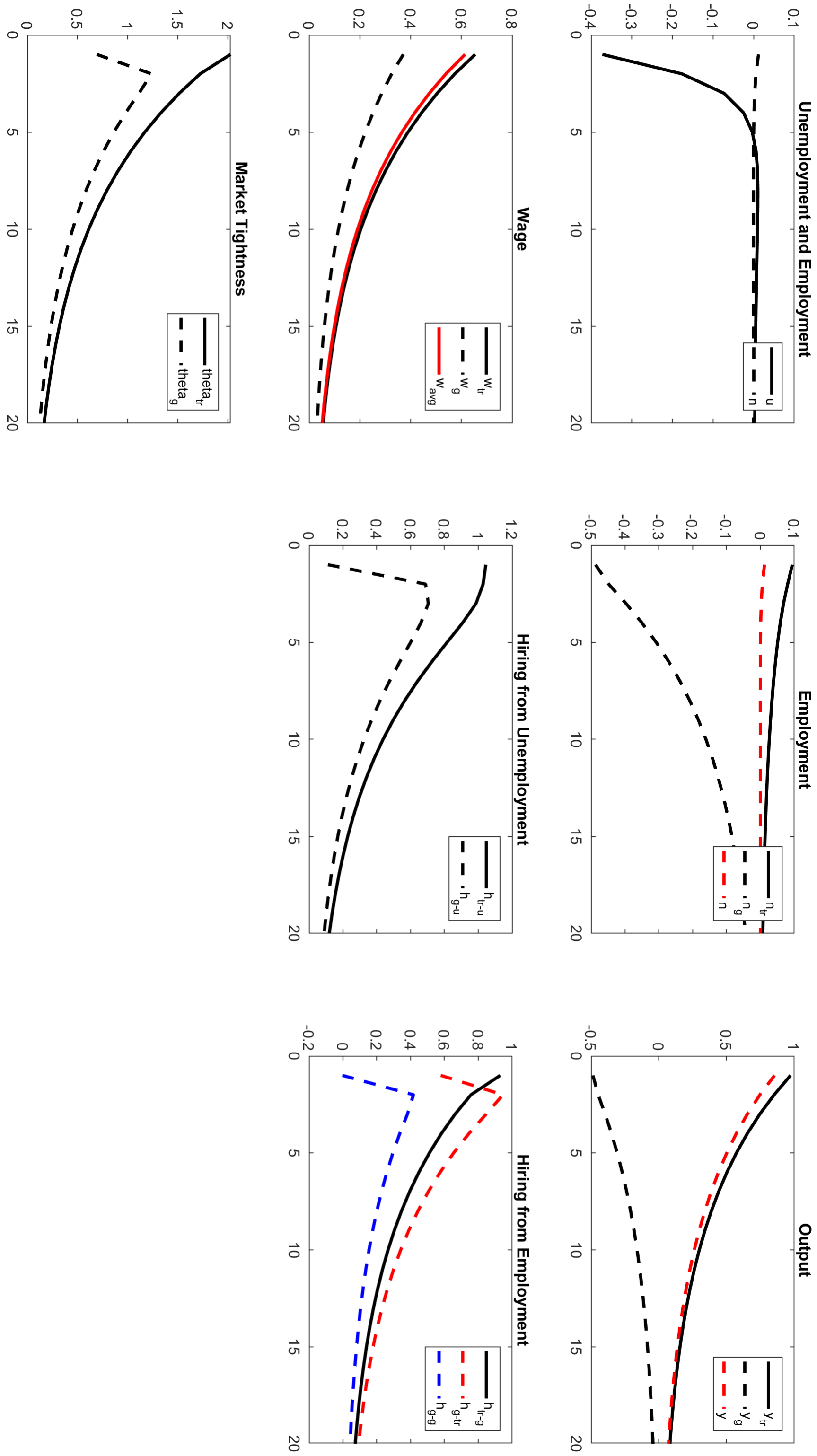

Figure 4.4: A Traditional Sector Productivity Shock

traditional-to-gig job transition. Workers make the gig-to-traditional job transition to fill the vacancies left behind by workers in traditional-to-gig transition, and hiring from unemployment falls. Examining Figs. 4.2) - 4.5), a pattern seems to emerge: where a shock induces a large increase in aggregate output, there is hiring on the job and from unemployment, but where the shock induces a small aggregate output increase, the unemployed are crowded out by job-changers.

Now turning to wages and output, Fig. 4.2) shows that in response to an aggregate demand shock, the transition of workers from gig to traditional employment is greater than the transition from traditional to gig or within gig employment. Hiring from unemployment largely falls. These result in a contraction of the gig sector which moderates the positive impact of the aggregate demand shock on aggregate output. Also, in response to aggregate demand shocks, firms create more vacancies. This means that market tightness increases and the wage increases, but to varying extents in both sectors. The impulse response for the wage in Fig. 4.2) reflects the relationship described in the wage equations in (4.36) and (4.37); the traditional sector wage can be weighed down by the gig sector as the gig sector wage is improved by the traditional sector. Fig. 4.2) also shows the moderating effect of the gig and traditional sectors on aggregate output and the average wage in response to an aggregate demand shock.

The moderating impact on aggregate output and the wage brought on by the presence of the gig economy is present for all other shocks, but to varying extents because of the marked difference in size between the gig and traditional sectors. I find that as the traditional and gig sectors become equal in size and number of workers, shocks no longer contract the gig sector, but the moderating effect of the gig sector on the macroeconomy becomes more prominent.[26] Put together, the results show how the UK gig economy helps explain slow wage and output growth.

4.10 Conclusion

Gig work is potentially the future of employment, but it may not be without consequences. A significant amount of attention is being paid to the increasing number of gig workers, but there is much less research on the flows between the gig and traditional sectors, their respective output contribution or the macroeconomic impact. I have begun to fill this gap.

I have shown that gig work can be a stepping-stone to traditional employment and vice versa, but it can make job-finding difficult for the unemployed. This suggests that, under some circumstances, gig working in the UK can become self-perpetuating: if workers who might have remained or become unemployed in the absence of the gig sector can instead shuttle between sectors and gain an advantage over the unemployed, then workers would take any job rather than remain or become unemployed. This might reduce unemployment, but it would potentially reduce wages and the quality of work as the gig economy expands.

Relatedly, workers taking on gig work after losing, or because they cannot find a traditional job, might disguise unemployment and over-state the level of employment. To accurately assess the labour market condition in an economy with a large gig sector, it may be necessary to prioritise underemployment and workers' reasons for engaging in gig work.

The results show that the presence of the gig economy changes the macroeconomic response to shocks. The model shows that gig workers earn a lower wage than traditional workers doing the same job because of differences in bargaining power and productivity. If these disparities between both sectors increase and the gig sector expands, the labour market might become composed of a large number of workers engaging in low-paid, low productivity work. This implies that the aggregate output, productivity and wage growth can slow down or fall even when the output, productivity and wage in the traditional sector

[26] See Appendix 3 for the results of the scenario in which the gig and traditional sectors are equal.

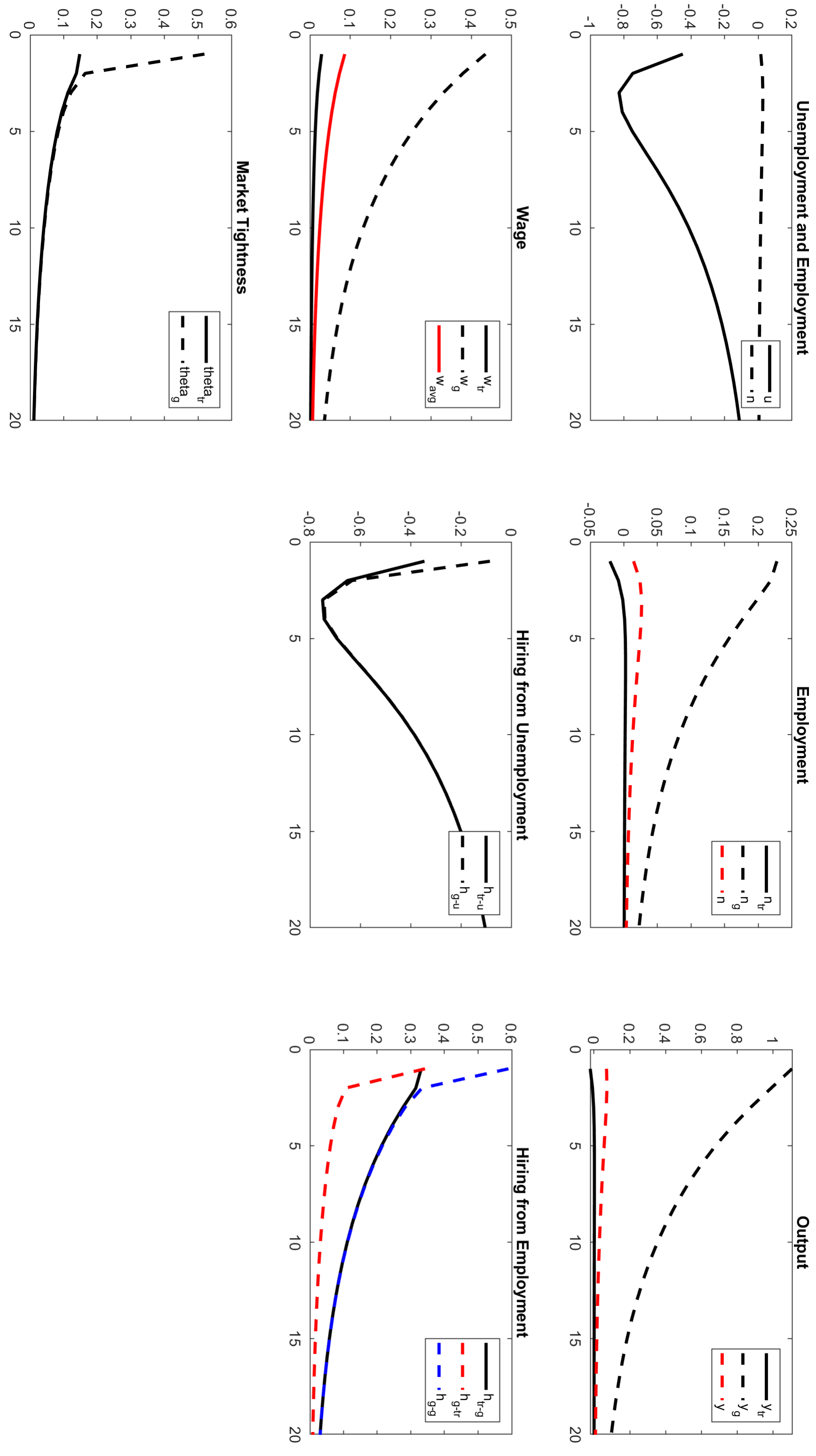

Figure 4.5: A Gig Sector Productivity Shock

may be rising, due to the change in the composition of the labour market. In addition, the moderating impact of shocks due to the presence of the gig economy, and, in particular, the contraction of the gig sector in response to an aggregate demand shock suggests that the effect of policies might be muted, or even distorted. This also suggests that it might be necessary for policy-makers to ensure that the gig sector keeps up with the traditional sector with productivity enhancing training, initiatives and technologies, and policies that enhance the conditions of work in the gig sector.

In future work, I will explore the impact of the rising gig economy on inflation and the implications for policy-making, job and skill polarisation, underemployment, labour force and gender participation and exposure to competition from the global labour market.

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Appendix

.1 Appendix: Wage Determination

.1.1 Wage Determination in the Low Productivity Wholesale Firm

We assume that wage bargaining takes place between the firm and non-graduates.[27] The bargained wage is determined by the sharing rule

$$(1-\zeta^l)S_t^{l,ng} = \zeta^l F_t^l \tag{47}$$

where $S_t^{l,ng}$ is the surplus to the household from an additional non-graduate being employed in a low productivity firm, F_t^l is the surplus to the firm and ζ^l is the bargaining power of non-graduates in the low productivity sector.

The firm's surplus is $F_t^{l,ng} = \frac{\partial J_t^l}{\partial N_t^{l,ng}}$. Because of the assumption of constant returns, we can combine this with the optimality condition for low productivity firms to obtain

$$F_t^l = \frac{P_t^{l,W}}{P_t^l}A_t^l - w_t^{b,l} + E_t\rho_t^{l,ng}\frac{\gamma^l}{q_{t+1}^l} \tag{48}$$

and

$$E_tF_{t+1}^l = \frac{\gamma^l}{E_tq_{t+1}^l} \tag{49}$$

The surplus the household derives from successful conclusion of the wage bargain, which is employment of an additional non-graduate at the low productivity firm less the outside option of that worker, which is being unemployed. So

$$S_t^{l,ng} = \frac{1}{C_t^{-\gamma}}\left(\frac{\partial H_t}{\partial n_t^{l,ng}} - \frac{\partial H_t}{\partial u_t^{ng}}\right) \tag{50}$$

Since $\frac{\partial H_t}{\partial n_t^{l,ng}} = C_t^{-\gamma}w_t^{b,l} + \rho_t^{l,ng}\frac{\partial H_t+1}{\partial n_{t+1}^{l,ng}}$ and $\frac{\partial H_t}{\partial u_t^{ng}} = C_t^{-\gamma}b_t + f_{t+1}^{l,ng,u}\frac{\partial H_{t+1}}{\partial n_{kt+1}^{l,ng}}$, where k denotes an alternative low productivity firm, the successful conclusion of the wage bargain implies that the household gains an additional non-graduate employed at a low productivity firm; this persists into the next period with probability $\rho_t^{l,ng}$. But the household loses an unemployed non-graduate, who would have moved into alternative employment in the low productivity sector at the beginning of the next period with probability $f_{t+1}^{l,ng,u}$. This implies

$$S_t^{l,ng} = w_t^{b,l} - b + (\rho_t^{l,ng} - f_{t+1}^{l,ng,u})E_t\beta_{t,t+1}S_{t+1}^{l,ng} \tag{51}$$

The sharing rule in (47) implies that the household surplus can be written as

$$\zeta^l F_t^l = (1-\zeta^l)(w_t^{b,l} - b) + \zeta^l E_t\beta_{t,t+1}(\rho_t^{l,ng} - f_{t+1}^{l,ng,u})F_{t+1}^l \tag{52}$$

Using (48) and (49) respectively, we obtain

$$\zeta^l\left\{\frac{P_t^{l,W}}{P_t^l}A_t^l - w_t^{b,l} + E_t\rho_t^{l,ng}\beta_{t,t+1}\frac{\gamma^l}{q_{t+1}^l}\right\} = (1-\zeta^l)(w_t^{b,l} - b) + \zeta^l E_t\beta_{t,t+1}(\rho_t^{l,ng} - f_{t+1}^{l,ng,u})\frac{\gamma^l}{q_{t+1}^l} \tag{53}$$

Using $f_t^{l,ng,u} = \zeta^{l,ng,u}f_t^l$, we obtain

$$w_t^{b,l} = \zeta^l\left\{\frac{P_t^{l,W}}{P_t^l}A_t^l + \gamma^l\zeta^{l,ng,u}E_t\beta_{t,t+1}\theta_{t+1}^l\right\} + (1-\zeta^l)b \tag{54}$$

[27] Although graduates and non-graduates have the same productivity and must be paid the same wage, a match with a non-graduate has a different value to a low productivity firm than a match with a graduate, because the respective matches break down with different probabilities.

.1.2 Wage Determination in the High Productivity Wholesale Firm

We assume that wages for high productivity jobs are determined through Nash bargaining between high productivity wholesale firms and graduates. The bargained wage is chosen to maximise

$$S_t = (S_t^h)^{\zeta^h}(F_t^h)^{1-\zeta^h} \tag{55}$$

where S_t^h is the surplus to the household from an additional graduate being employed in a high productivity firm, F_t^h is the surplus to the firm and ζ^h is the bargaining power of graduates in high productivity jobs. This gives the sharing rule

$$(1-\zeta^h)S_t^h = \zeta^h F_t^h \tag{56}$$

The surplus for a representative high productivity firm is

$$F_t^h = \frac{\partial J_t^h}{\partial n_t^h} \tag{57}$$

Combining this with the optimality conditions gives

$$F_t^h = \frac{P_t^{h,W}}{P_t^h}A_t^h - w_t^{b,h} + E_t\rho_t^h\frac{\gamma^h}{q_{t+1}^h} \tag{58}$$

and

$$E_tF_{t+1}^h = \frac{\gamma^h}{E_tq_{t+1}^h} \tag{59}$$

The surplus the household derives from successful conclusion of the wage bargain, which is employment of a graduate household member at the high productivity firm less the outside option of that worker, which is being unemployed. So

$$S_t^h = \frac{1}{C_t^{-\gamma}}\left(\frac{\partial H_t}{\partial n_t^h} - \frac{\partial H_t}{\partial u_t^g}\right) \tag{60}$$

The successful conclusion of the wage bargain implies that the household gains an additional graduate employed at a high productivity firm; this match persists into the next period with probability ρ_t^h. But the household loses an unemployed graduate, who would have moved into alternative employment in the high productivity sector with probability $f_{t+1}^{h,g,u}$ or alternative employment in the low productivity sector with probability $f_{t+1}^{l,g,u}$. This implies $\frac{\partial H_t}{\partial n_t^h} = C_t^{-\gamma}w_t^{b,h} + \rho_t^h\frac{\partial H_t+1}{\partial n_{t+1}^h}$ and $\frac{\partial H_t}{\partial u_t^g} = C_t^{-\gamma}b_t + f_{t+1}^{h,g,u}\frac{\partial H_{t+1}}{\partial n_{kt+1}^h} + f_{t+1}^{l,g,u}\frac{\partial H_{t+1}}{\partial n_{k't+1}^{l,g}}$, where k here denotes an alternative high productivity firm and k' denotes a low productivity firm. As all high productivity firms are identical and all low productivity firms are identical, this implies

$$S_t^h = w_t^{b,h} - b + E_t\beta_{t,t+1}(\rho_t^h - f_{t+1}^{h,g,u})S_{t+1}^h - E_t\beta_{t,t+1}f_{t+1}^{l,g,u}S_{t+1}^l \tag{61}$$

The sharing rules in (47) and (56) imply that the household surplus can be written as

$$\zeta^hF_t^h = (1-\zeta^h)w_t^{b,h} - b + \zeta^hE_t\beta_{t,t+1}(\rho_t^h - f_{t+1}^{h,g,u})F_{t+1}^h - \zeta^hE_t\beta_{t,t+1}f_{t+1}^{l,g,u}F_{t+1}^l \tag{62}$$

Using (49), (58) and (59), we obtain

$$\zeta^h\left\{\frac{P_t^{h,W}}{P_t^h}A_t^h - w_t^{b,h} + E_t\beta_{t,t+1}\rho_t^h\frac{\gamma^h}{q_{t+1}^h}\right\} = (1-\zeta^h)(w_t^{b,h}-b) + \zeta^hE_t\beta_{t,t+1}(\rho_t^h - f_{t+1}^{h,g,u})\frac{\gamma^h}{q_{t+1}^h} - \zeta^hE_t\beta_{t,t+1}f_{t+1}^{l,g,u}\frac{\gamma^l}{q_{t+1}^l} \tag{63}$$

Simplifying this

$$w_t^{b,h} = \zeta^h \left\{ \frac{P_t^{h,W}}{P_t^h} A_t^h + \gamma^h E_t \theta_{t+1}^h + \gamma^l E_t \theta_{t+1}^l \right\} + (1 - \zeta^h) b \tag{64}$$

Noting that $f_t^{h,g,u} = \zeta^{h,g,u} f_t^h$ and $f_t^{l,g,u} = \zeta^{l,g,u} f_t^l$ gives

$$w_t^{b,h} = \zeta^h \left\{ \frac{P_t^{h,W}}{P_t^h} A_t^h + \gamma^h \zeta^{h,g,u} E_t \theta_{t+1}^h + \gamma^l \zeta^{l,g,u} E_t \theta_{t+1}^l \right\} + (1 - \zeta^h) b \tag{65}$$

.2 Appendix

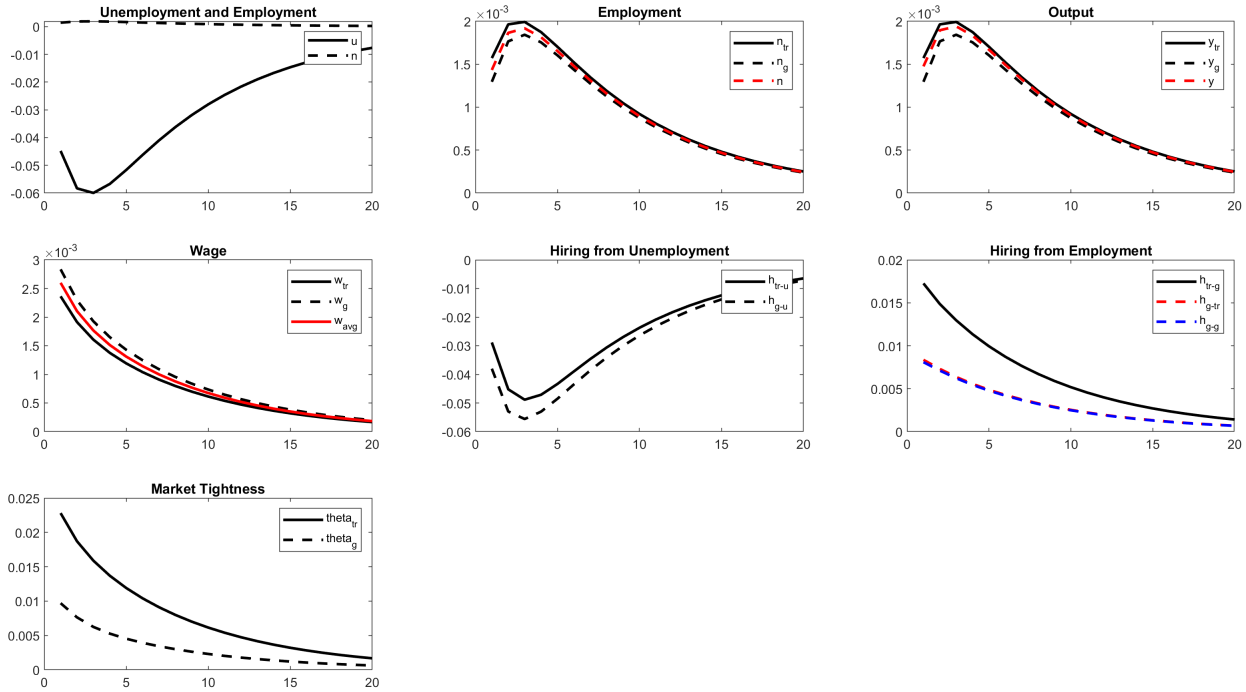

Figure 6: Aggregate Demand Shock with Equal Gig and Traditional Sectors

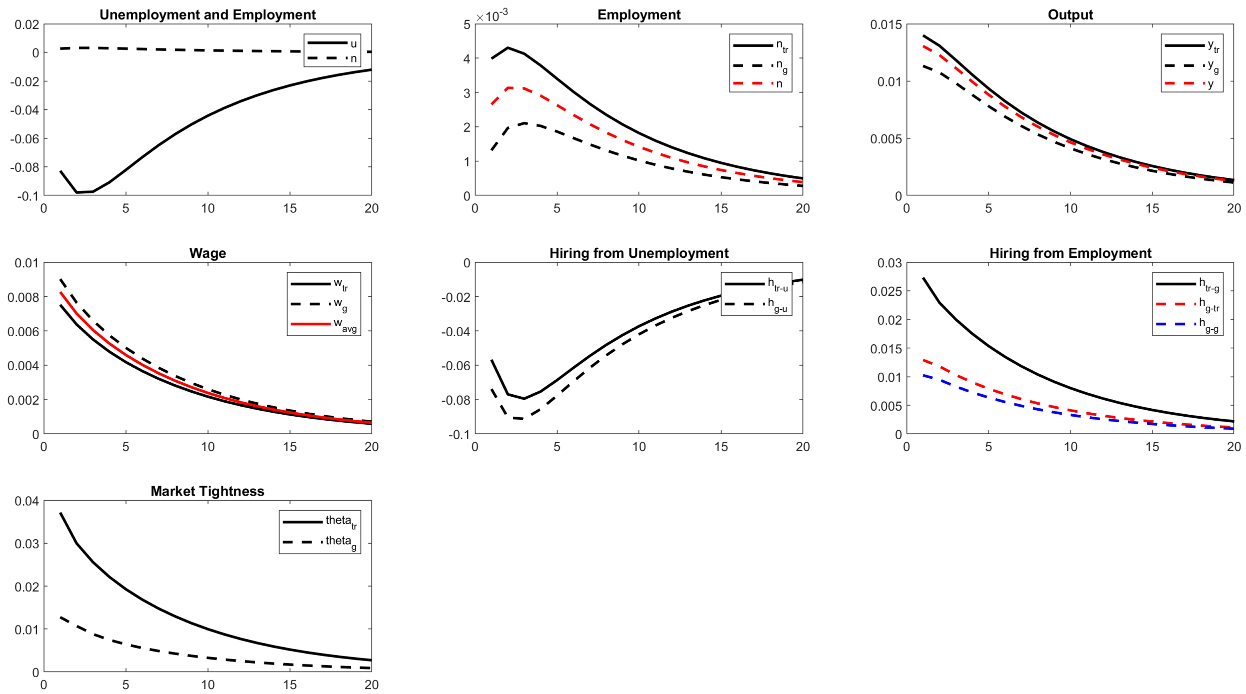

Figure 7: Aggregate Supply Shock with Equal Gig and Traditional Sectors

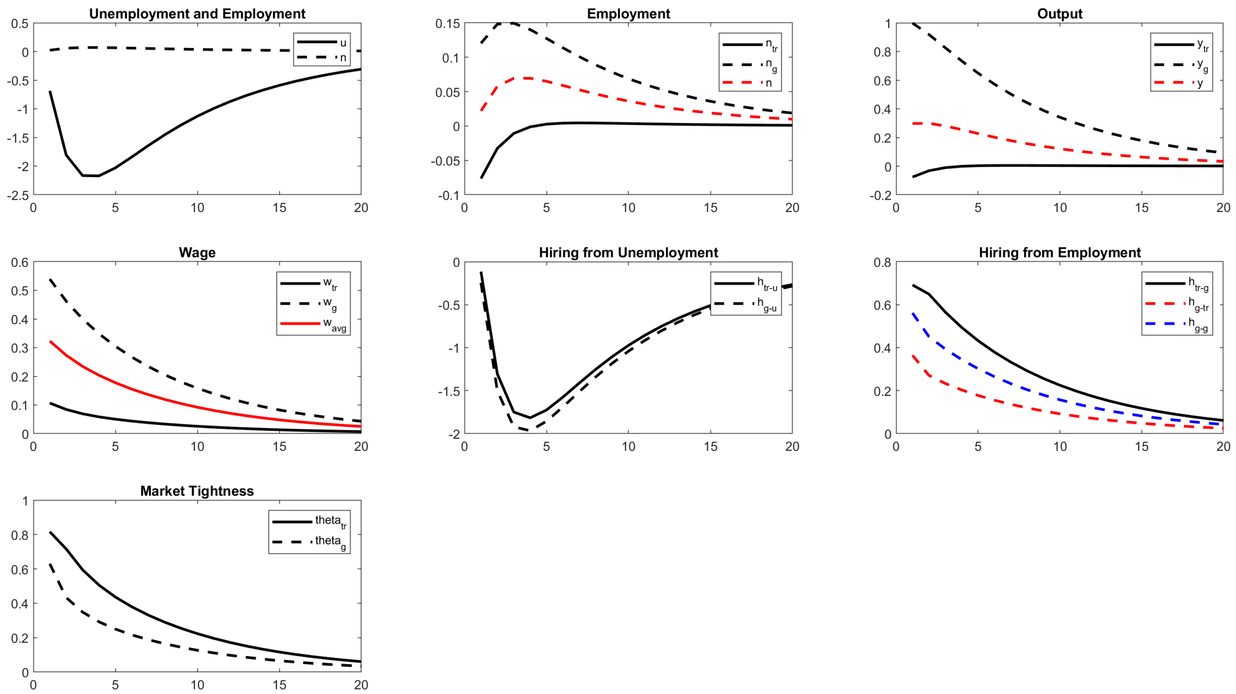

Figure 8: Gig Sector Supply Shock with Equal Gig and Traditional Sectors

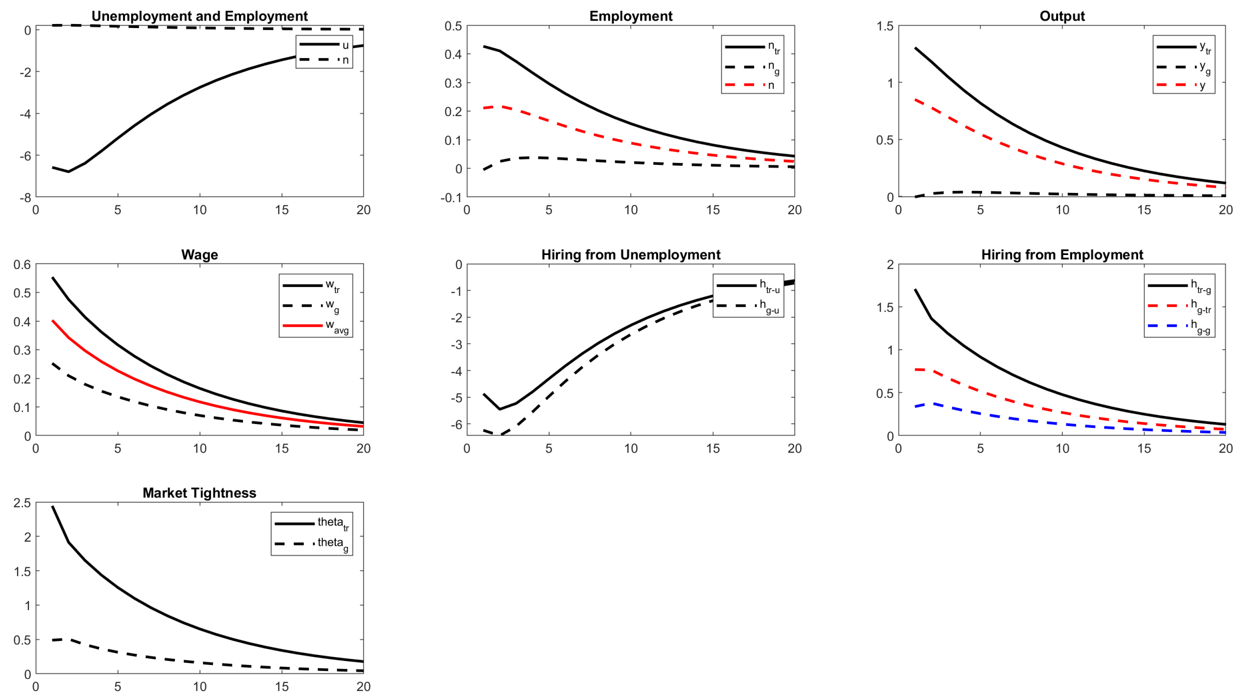

Figure 9: Traditional Sector Supply Shock with Equal Gig and Traditional Sectors